Organizational Form and River Quality: Theory and Evidence from China

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Abstract

Should the government set up a separate ministry for all environmental issues, or ask all the existing decentralized and regional political organizations to have an environmental mandate? This paper studies how organizational forms incentivize political agents to internalize environment-related externalities. The theory of M-form versus U-form organizations features negative spillovers among different bureaucratic tasks, as well as spatial pollution externality that one region generates to another. I show that M-form reform may deliver better environmental performance only when spatial pollution externality is less salient and task spillover is stronger. I further argue that yardstick competition, conventionally viewed as an advantage of M-form, may exacerbate the environmental problem. I examine the empirical setting of River Chief System in China as a shift from U-form to M-form in river management. With water quality observations from monitoring stations and environmental management information from 2015 to 2020, the empirical results highlight the heterogeneous effects of M-form reform on river quality, which are largely consistent with the theoretical predictions. I also find greater investment in water treatment infrastructure and growing instances of Coasian coordination across regions in more recent years, underscoring the importance of organizational design for environmental governance.

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1 Introduction

Governments across the world have established specialized environmental ministries, a practice that spread from a handful of countries around 1970 to roughly 86% of countries by the turn of the century (Figure 1)[1]. But is it always desirable to assign environmental responsibility *primarily* to a separate ministry, or give the existing decentralized and regional organizations an environmental mandate[2]? The answer is far from obvious, for at least two reasons. First, political agents face multiple and often conflicting tasks: reducing pollution typically constrains growth opportunities, particularly in developing economies reliant on polluting industries. Second, environmental problems are inherently spatial: pollution generated in one region spills over into neighboring regions along rivers or through the air. Different organizational forms imply distinct incentive structures for addressing these externalities, and the optimal design of environmental governance can be context-specific.

This paper exploits a rare, large-scale natural experiment, i.e., the nationwide rollout of China's River Chief System (RCS), to answer this question. Despite the global trend in establishing dedicated environmental ministries, the RCS re-bundles the responsibility for cleaning up rivers from the specialized body into the portfolios of general-purpose local leaders, at least *de jure*. This setting allows us to study, both theoretically and empirically, when each organizational form better internalizes environmental externalities and reduces water pollution.

I conceptualize the RCS reform as a shift from a functionally specialized U-form toward an integrated regional M-form (Chandler, 1987; Williamson, 1975; Maskin et al., 2000; Qian et al., 2006)[3]. Under the U-form, a central environmental ministry manages environmental performances across all regions, while economic development is delegated to separate government bodies. Under the M-form, regional governments are responsible for both economic development and environmental protection within their jurisdictions. I abstract from information asymmetry that previous literature emphasizes, and instead focus on how these two organizational forms incentivize political agents to internalize two key externalities. The first is a *task externality*: performance on one task affects performance on the other within a region, since economic activities can affect pollution outcomes and vice versa. The second is a *regional pollution externality*, capturing the fact that pollutants flow from upstream to downstream regions [4].

I develop a simple theoretical framework to characterize which organizational form delivers better environmental and economic outcomes. The key insight is that each organizational form internalizes only one type of externality, so neither achieves the first-best outcome. Under the U-form, the central ministry internalizes the regional pollution externality, i.e., it cares about environmental performances across all regions; but it ignores the task externality, since economic development lies outside its mandate. Under the M-form, regional governors optimize over both economic and environmental outcomes within their jurisdictions, internalizing the task externality, but neglect the pollution spillovers they

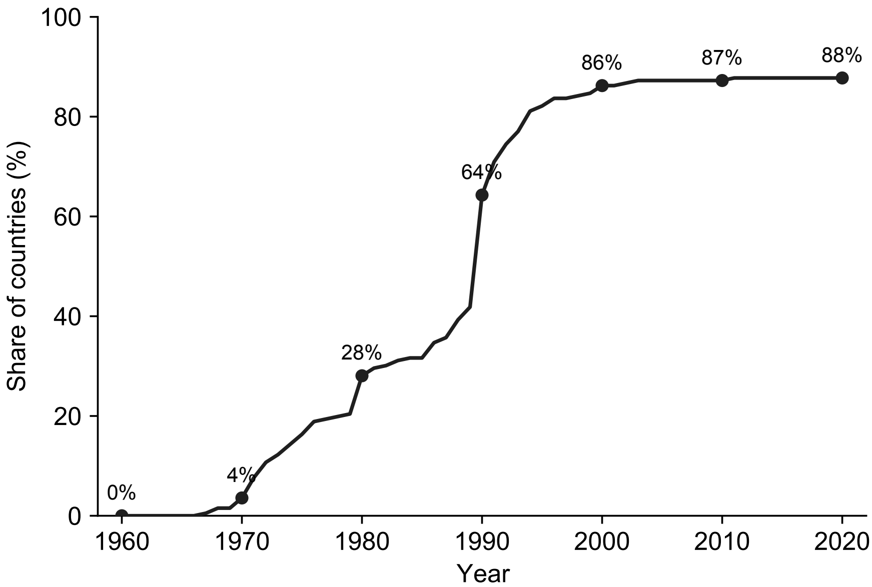
[1]For example, the United Kingdom created the world's first minister of environment in 1970. In the United States, by contrast, environmental authority remains distributed across the federal level (notably the EPA) and decentralized state-level agencies.

[2]In practice, these organizational forms are not mutually exclusive. But the relevant question for this paper is where primary, *de jure* responsibility for environmental performance is assigned because it shapes incentives at the margin.

[3]A canonical illustration is the contrast between the Soviet Union, where bureaucratic activities were organized under specialized functional ministries (U-form), and post-reform China, with regional governance bodies competing against each other (M-form), i.e., a comparison often invoked to explain their divergent economic performances.

[4]One might invoke the Coase Theorem to argue that these externalities can be resolved through bargaining between upstream and downstream governments, rendering organizational form irrelevant. Chen et al. (2025) document such Coasian compensation initiatives in China. However, as I will show in Section 4.4.3, these practices were still nascent and far from widespread during our sample period.

Figure 1: The establishment of national environmental/climate ministries, 1960–2020



Notes: The vertical axis reports the cumulative share of countries that had established a dedicated national environmental or climate ministry by a given year among all 196 countries in the sample. We include the ministries if their names specialized in *Environment* and/or *Climate*. National committee, council, public authority, and agency are excluded. This figure is constructed from the lead environmental authority by country information from the United Nations Environment Programme (https://wedocs.unep.org/items/d2308346-46e2-4d34-afd9-024f53c96de4); establishment years are manually collected from official government and archival sources.

impose downstream. The second-best organizational form therefore depends on the intensity of the two externalities: M-form dominates when the task externality is stronger and the regional pollution externality is less salient. In other words, the M-form reform trades better within-region coordination for worse cross-region coordination, and its effectiveness is therefore context-specific, a prediction I bring to the data.

The classic argument in favor of M-form organization emphasizes the role of yardstick competition in incentivizing agents to exert effort (Maskin et al., 2000). I show, however, that in the presence of asymmetric spatial pollution externalities, relative performance evaluation can exacerbate rather than ameliorate the environmental problem. The intuition is straightforward: since pollution flows one way, from upstream to downstream, the upstream agent gains a strategic advantage by relaxing its own pollution abatement effort, degrading its downstream competitor's environmental performance and widening the relative performance gap. Yardstick competition thus creates an additional distortion, incentivizing upstream agents to over-pollute beyond the baseline M-form. Furthermore, the effect of competition on pollution reduction from the baseline U-form to the M-form with yardstick competition is theoretically ambiguous: stronger competition raises both economic and environmental effort, so the net outcome depends on which force dominates, leaving another open empirical question to explore.

I use the empirical setting of the River Chief System in China to test these theoretical predictions. Rolled out nationwide between 2016 and 2018, the RCS reassigned formal responsibility for improving river quality from the Ministry of Water Resources and its regional bureaus to senior local leaders who were previously evaluated mainly on local GDP (Li and Zhou, 2005); it therefore, at least *de jure*, converts river management from a U-form into an M-form. I then use a staggered difference-in-differences design to identify the effect of RCS adoption at the city level on river quality. I construct a dataset covering water quality observations from geo-coded monitoring stations across China over

2015–2020, merged with river management records and bureaucratic characteristics manually collected from government websites. The primary outcomes are three water quality indicators, namely dissolved oxygen (DO), permanganate index (COD_{Mn}), and ammonia nitrogen (NH_3-N), from which I also construct a standardized pollution index following Anderson (2012) and Schwab et al. (2020).

Guided by the theoretical framework, I explore the average and heterogeneous effects of the M-form reform along four dimensions, each mapped to an empirical proxy. First, the intensity of spatial pollution externality (δ) is proxied by average city land slope, since flatter terrain slows river flow and reduces cross-regional pollutant transport. The intensity of task externality (λ_2) is proxied by the service-sector share of local GDP, since a more service-oriented economy entails a weaker development–pollution tradeoff in the industrial and agricultural pollutants that our water quality indicators measure. I proxy the cost of environmental effort (w) by river chief educational attainment, since environmental management can be intensive in specialized knowledge and hence more educated chiefs face a lower cost of abatement effort. Finally, the intensity of political competition (σ) is proxied by within-province age dispersion among river chiefs[5], with lower dispersion of age indicating more intense head-to-head political competition for promotion.

The empirical results largely support the theoretical predictions. On average, RCS adoption improves river quality gradually, with the composite pollution index falling by around 0.3-1.0 standard deviations by the sixth month post-adoption. The directions of heterogeneous effects are also consistent with the theory: pollution reductions are the largest exactly where the model says the M-form should excel, i.e., in cities with flatter terrain, where cross-regional spillovers are weak, and in cities reliant on polluting industry and agriculture, where the within-region task externality is strong. Cities led by river chiefs with master's degree also exhibit larger reductions than those with less educated chiefs. The role of political competition is more nuanced, but still consistent with the theoretical ambiguity: while high-competition cities exhibit greater improvements in dissolved oxygen, which responds more readily to enforcement-based abatement, low-competition cities show larger reductions in ammonia nitrogen, which reflects that more diffuse agricultural sources are harder to abate through direct enforcement so that the over-pollution channel dominates.

Several additional results support the robustness of our findings. To address potential bias from spatial pollution spillovers violating the SUTVA assumption, I construct a spatially thinned subsample of monitoring stations and re-estimate the average and heterogeneous effects. The results are broadly consistent with the full-sample findings, but with slightly larger magnitude, particularly in contexts where the theory predicts larger gains from M-form reform. This is consistent with the direction of bias induced by spatial spillovers: improvements in water quality in upstream treated cities benefit downstream control cities, compressing the treatment-control difference and biasing the full-sample estimates toward zero. Secondly, to isolate the effect of the de jure organizational form change from confounding personnel changes, I augment the baseline specification with fixed effects for both the river chief and the provincial water resources director, and find slightly larger treatment effect estimates. This suggests that the bureaucratic turnover correlated with the timing of RCS adoption, if anything, works against the reform; hence the baseline estimates are conservative. Finally, replacing the baseline proxies for externality intensity with alternative measures, namely, a composite index of land slope and river sinuosity for spatial pollution externality, and wastewater intensity of industrial production for task spillovers, yields qualitatively similar heterogeneity results.

I also document a richer picture of how M-form reform operates and where its limits lie. RCS

[5] Age is one of the core determinants of promotion likelihood in the Chinese political system (Xu, 2011; Wang et al., 2020). If all river chiefs are similar in age, their competition over environmental performance is likely to be more intense.

appears to be associated with durable improvements in wastewater treatment capacity beyond the short-run effects captured by the event study estimates. Secondly, the reform's effects extend partially to air quality, reducing industrial gaseous pollutants which is consistent with river chiefs imposing stricter environmental regulations on polluting firms. I also find a slight increase in particulate matter following RCS adoption, which suggests that organizational reforms with narrowly targeted mandates may have unintended consequences on non-targeted dimensions (Kahn et al., 2015). Finally, voluntary coordination among river chiefs to internalize cross-regional externalities does emerge in later years, but it remains small in scale and confined within provincial boundaries. Organizational design therefore remains a first-order determinant of environmental outcomes.

Related Literature This paper is related to three strands of literature. The first concerns the political economy of pollution mitigation (Sigman, 2002; Ostrom, 2015). Lipscomb and Mobarak (2017) document that pollution near county boundaries increased with the decentralization and splitting of counties in Brazil, and argue that institutional factors such as river basin committees and shared party affiliations help mitigate cross-border externalities. Kahn et al. (2015) exploit a policy change in China that incorporated water pollution into local officials' promotion criteria, and show that pollution at regional boundaries was reduced, though improvements were limited to the targeted dimensions. He et al. (2020) measure TFP losses from China's water regulation, showing that local officials impose tighter regulation on upstream firms near monitoring stations relative to downstream firms. Relative to this literature, I investigate how the organizational structure of river management shapes environmental outcomes at the national scale, and provide a theoretical framework for understanding when organizational reform is most effective in internalizing pollution externalities. A number of recent papers also study cross-regional coordination and specifically the River Chief System (Chen et al., 2025; Mu et al., 2025; Liu et al., 2024; Li et al., 2020; Chen et al., 2018; Cai et al., 2016). I show, both theoretically and empirically, that the change in organizational form through RCS is itself a first-order determinant of water quality improvement, and that its effectiveness is heterogeneous in precisely the directions the theory predicts.

The second strand concerns the theoretical literature on organizational forms. Maskin et al. (2000) argue that M-form promotes yardstick competition and provides stronger managerial incentives than U-form, applying the theory to China's transition experience. Qian et al. (2006) show that M-form facilitates experimentation and innovation through decentralized coordination. Aghion and Tirole (1995) introduce overload considerations into the choice of organizational form. I contribute to this literature by introducing environment-related externalities into a framework that compares organizational forms, and showing that yardstick competition, typically viewed as an advantage of M-form, may exacerbate rather than ameliorate environmental problems in the presence of asymmetric spatial spillovers.

More broadly, this paper contributes to the political economy of environmental governance and the organizational economics of the state (Besley et al., 2022). For example, Burgess et al. (2012) show how political fragmentation leads to more deforestation in Indonesia, and Jia (2024) shows that political connections increase local governments' tolerance for pollution in China. This paper is also related to the economic impact of decentralization (see Gadenne and Singhal (2014) for a review)[6]. I emphasize the distinction of whether environmental authority should be decentralized along functional or regional lines (holding the level of government fixed), and provide causal evidence for this from a

[6]See Kong and Liu (2024) for evidence that centralizing the appointment of local environmental bureaucrats strengthens enforcement and improves air quality.

large-scale organizational reform.

The remainder of this paper is organized as follows. Section 2 develops the theoretical framework and derives the main predictions. Section 3 provides institutional background and data description. Section 4 presents the empirical results. Section 5 concludes.

2 A Theory of Organizational Forms

2.1 The Core Model

We consider two regions $r \in \{A, B\}$ along a river, where region A is upstream and region B is downstream. Political agents (e.g., bureaucrats) have two tasks $i \in \{1, 2\}$, where task 1 is developing the economy and task 2 is protecting the environment (e.g., the river). The effort choice of political agents is denoted as $e_{ir} \in [0, 1]$.

The performance on each task depends on the agents' effort choices. The performance of developing the economy in region r is given by [7]

$$Y_r = f(e_{1r}) - \lambda_1 g(e_{2r}), \tag{1}$$

where $f(e)$ and $g(e)$ are both increasing and concave in e, and $f(0), g(0) \geq 0$. The first term captures the direct return to economic effort. The second reflects the effect of increasing environmental effort on reducing economic performance, with $\lambda_1 \in [0, 1]$ governing its magnitude. This reflects the tradeoff that stricter environmental enforcement often curtails polluting industries, which may reduce economic performance.

The pollution level (i.e., environmental performance) in upstream region A is

$$Q_A = \lambda_2 f(e_{1A}) - g(e_{2A}), \tag{2}$$

where $\lambda_2 \in [0, 1]$ governs the extent to which economic development raises local pollution. The second term says that higher environmental effort reduces pollution. Downstream pollution in B depends on not only local effort choices, but the pollutant inflows from upstream with a depreciation rate δ[8]:

$$Q_B = (1 - \delta)Q_A + \lambda_2 f(e_{1B}) - g(e_{2B}). \tag{3}$$

A higher δ implies that pollutants dissipate rapidly within the upstream region and contribute less to downstream pollution.

The cost of effort is $c(e) = \frac{1}{2}e^2$ for the economic task and $d(e) = \frac{1}{2}\omega e^2$ for environmental protection, where $\omega \in [1, \overline{\omega}]$ is the relative difficulty of improving environmental performance. For instance, protecting the rivers requires more advanced or specialized knowledge in environmental management such that agents with higher education or greater experience in environmental issues face a lower ω.

We begin by characterizing the effort levels that maximize joint surplus, then analyze how incentives under different organizational forms deviate effort away from this optimum.

[7] We adopt the additive form for Y_r and Q_r for two reasons. First, it delivers clean closed-form characterizations of the effort distortions under each organizational form. Second, and more importantly, it isolates the externality-internalization channel as the sole driver of organizational performance differences: by shutting down cross-partial effects between tasks, it ensures that the ranking of organizational forms is determined entirely by how well each internalizes the two externalities, rather than by complementarities or substitutabilities in effort. However we can show that most of our main theoretical results extend to the general formulation $Y_r = y(e_{1r}, e_{2r})$ and $Q_r = q(e_{1r}, e_{2r})$ under standard regularity conditions on the cross-partial derivatives.

[8] Note that this is a simpler formulation of cross-border pollution externality in Lipscomb and Mobarak (2017).

Surplus Maximizing Choice of Efforts A planner chooses $\{e_{1A}, e_{2A}, e_{1B}, e_{2B}\}$ to maximize

$$S(e_{1A}, e_{2A}, e_{1B}, e_{2B}) = Y_A - Q_A + Y_B - Q_B - \frac{1}{2}(e_{1A})^2 - \frac{1}{2}\omega(e_{2A})^2 - \frac{1}{2}(e_{1B})^2 - \frac{1}{2}\omega(e_{2B})^2.$$

The first order conditions are

$$[1 - \lambda_2(2 - \delta)]f'(e^*_{1A}) = e^*_{1A} \tag{4}$$

$$[(1 - \lambda_1) + (1 - \delta)]g'(e^*_{2A}) = \omega\, e^*_{2A} \tag{5}$$

$$(1 - \lambda_2)f'(e^*_{1B}) = e^*_{1B} \tag{6}$$

$$(1 - \lambda_1)g'(e^*_{2B}) = \omega\, e^*_{2B} \tag{7}$$

To guarantee an interior solution, we impose

Assumption 1 $\lambda_2(2 - \delta) < 1$.

This says that the total pollution effect of economic activity (locally and via upstream spillover) should not be so large as to make upstream economic effort socially wasteful.

The last two conditions characterize optimal effort in downstream region B: the planner equates the marginal social benefit of effort to its marginal cost, where the terms $(1 - \lambda_1)$ and $(1 - \lambda_2)$ reflect internalization of the cross-task externality between economic activity and pollution reduction. The first two conditions characterize upstream region A: the coefficients on $f'(e^*_{1A})$ and $g'(e^*_{2A})$ each carry an additional $(1 - \delta)$ term, capturing internalization of the cross-region pollution externality imposed on the downstream region. A lower δ (less local dissipation) amplifies this term, inducing the planner to demand more environmental effort and less economic effort upstream to limit pollution outflows. Thus the surplus-maximizing effort profile fully internalizes both externalities: across tasks within a region, and across regions along the river.

I now analyze effort choices under different organizational forms and characterize how they deviate from the surplus optimum. The key tradeoff is that each organizational form internalizes only one type of externality, either across tasks or across regions, but not both. The problem then reduces to a second-best comparison: which organizational form delivers higher total surplus depends on the relative intensity of these two externalities, a distinction I bring to the data in the empirical analysis.

U-form Bureaucracy The U-form bureaucracy enforces task specialization among political agents: local leaders are responsible for economic development (task 1) and water resource bureaucrats for environmental protection (task 2). The local leader in region r chooses e_{1r} to maximize $Y_r - \frac{1}{2}e^2_{1r}$, yielding the first-order condition:

$$f'(e^U_{1r}) = e^U_{1r}. \tag{8}$$

Economic effort equates the marginal return to development to its marginal cost, taking environmental effort as given. However, the local leader does not internalize the effect of economic activity on pollution, since Q_r does not enter the objective.

The water resource bureaucrats jointly choose $\{e_{2A}, e_{2B}\}$ to maximize environmental performance (i.e., minimize total pollution $(Q_A + Q_B)$) net of effort costs:

$$-(Q_A + Q_B) - \frac{1}{2}\omega e^2_{2A} - \frac{1}{2}\omega e^2_{2B}.$$

The optimal environmental efforts satisfy:

$$(2-\delta)g'(e_{2A}^U) = \omega e_{2A}^U, \tag{9}$$
$$g'(e_{2B}^U) = \omega e_{2B}^U. \tag{10}$$

The downstream condition (10) is standard: environmental effort equates marginal pollution reduction to marginal cost. The upstream condition (9) features the additional $(1-\delta)$ term: the water bureaucrats internalize the cross-region externality[9], recognizing that upstream environmental effort reduces not only local pollution but also pollution inflows to the downstream region. However, U-form bureaucracy fails to internalize the cross-task externality: since economic and environmental outcomes enter separate objective functions, neither set of agents accounts for the effect of their effort on the other task. We return to this point when comparing organizational forms.

M-form Bureaucracy Under M-form bureaucracy, the river chief in each region is responsible for both tasks. The river chief in region A chooses $\{e_{1A}, e_{2A}\}$ to maximize

$$Y_A - Q_A - \frac{1}{2}e_{1A}^2 - \frac{1}{2}\omega e_{2A}^2,$$

yielding the first-order conditions:

$$(1-\lambda_2)f'(e_{1A}^M) = e_{1A}^M, \tag{11}$$
$$(1-\lambda_1)g'(e_{2A}^M) = \omega e_{2A}^M. \tag{12}$$

The river chief in region B solves a similar problem and the optimal efforts satisfy the same conditions:

$$(1-\lambda_2)f'(e_{1B}^M) = e_{1B}^M, \tag{13}$$
$$(1-\lambda_1)g'(e_{2B}^M) = \omega e_{2B}^M. \tag{14}$$

Two observations follow. First, M-form bureaucracy internalizes the cross-task externality: the river chief accounts for the effect of economic activity on pollution (and vice versa), reflected in the terms $(1-\lambda_2)$ and $(1-\lambda_1)$. Second, and in contrast to the surplus optimum, the upstream river chief ignores the cross-region externality: the pollution outflow $(1-\delta)Q_A$ to the downstream region does not enter region A's objective, so upstream effort choices are identical to those in region B[10]. M-form thus achieves within-region balance across tasks at the cost of failing to internalize cross-region spillovers.

Comparisons of Organizational Forms We now present our main results of comparative institutional analysis. We first introduce some additional assumptions:

Assumption 2 *We make the following regularity assumptions:*

(i) $\eta(e) \equiv e/g'(e)$ *is convex in* e*;*

(ii) Spatial externality is sufficiently salient: $\delta \leq \delta^* = 2 - \omega\chi^{-1}\left(\chi\left(\frac{1}{\omega}\right) + \kappa(1) - \kappa(0)\right)$[11].

[9] This is consistent with Kong and Liu (2024) who find that there is better internalization of inter-jurisdictional externalities among local environment bureaucrats appointed by provincial government in China, although focusing on air quality.

[10] However as we shall see below, there will be no such symmetry result for effort choices under yardstick competition between the two regions.

[11] We use the notation $\kappa(x) \equiv f(\theta^{-1}(x))$ and $\chi(x) \equiv g(\eta^{-1}(x))$ where $\theta(e) \equiv e/f'(e)$ and $\eta(e) \equiv e/g'(e)$, both increasing by concavity of f and g.

Assumption 2(i) is a mild regularity condition on the curvature of the environmental performance function satisfied by a wide class of standard functional forms for $g(e)$, which requires that the marginal abatement benefit of environmental effort diminishes sufficiently fast[12]. We now discuss how incentives and performances under U-form deviate from the surplus optimum, summarized by the following proposition:

Proposition 1 *Suppose Assumption 1 holds. Under U-form, both economic and environmental effort exceed the surplus optimum in both regions: $e_{1r}^U \geq e_{1r}^*$ and $e_{2r}^U \geq e_{2r}^*$ for $r \in \{A, B\}$. Both pollutant gap, i.e., $Q_r^U - Q_r^*$, and economic performance gap, i.e., $Y_r^U - Y_r^*$, are increasing in λ_2 and decreasing in λ_1. If in addition Assumption 2(i) holds, both the pollution gap $Q_A^U - Q_A^*$ and economic performance gap $Y_A^U - Y_A^*$ are decreasing in δ. The pollution gap in downstream is also decreasing in δ if upstream over-pollutes.*

We leave the proof for all propositions in the Appendix. Under U-form, neither set of agents internalizes the cross-task externality. Local leaders ignore the pollution cost of economic activity (λ_2 absent from their objective), leading to excess economic effort; water bureaucrats ignore the drag that environmental effort imposes on economic performance (λ_1 absent from their objective), leading to excess environmental effort. It is important to highlight that in this model the core problem of organizational design is not about providing high-powered incentives to agents, but better internalization of different externalities where agents appropriately **lower** their effort choices[13].

A larger λ_2 amplifies both performance gaps. Since economic activity is more polluting, the surplus optimum demands lower economic effort; U-form ignores this, so the excess economic effort generates more pollution and higher economic output relative to the optimum. A higher λ_1, by contrast, compresses both gaps in the opposite direction. Since environmental effort is more costly to economic output, the surplus optimum demands lower environmental effort. Agents under U-form ignore this and maintain excessive environmental effort, which suppresses economic output and reduces pollution relative to the optimum, shrinking both $Y_r^U - Y_r^*$ and $Q_r^U - Q_r^*$.

As δ falls, pollutants dissipate less within the upstream region and contribute more to downstream pollution, so the surplus optimum tightens upstream standards on both margins: it demands less economic effort (to limit pollution generation) and more environmental effort (to limit outflows to the downstream region). Under U-form, economic effort does not respond to δ at all, so the economic effort gap widens and generates more excess pollution upstream. Environmental effort does respond to δ with water bureaucrats internalizing the cross-region externality with $g(e_{2A}^*) < g(e_{2A}^U)$, i.e., the U-form over-abates pollution which at least partially offsets the pollution from excess economic effort. Assumption 2(i) guarantees that when δ falls, the marginal increase of e_{2A}^* is higher than that of e_{2A}^U given $e_{2A}^U > e_{2A}^*$. This means the U-form's over-abatement relative to the optimum shrinks, reducing the offset against excess pollution from the economic channel. Hence overall upstream pollution gap $Q_A^U - Q_A^*$ widens as δ falls. For the downstream region, the effect is further amplified: not only is there more upstream excess pollution, but a larger share $(1 - \delta)$ of it flows into the downstream region.

The sign of $Q_r^U - Q_r^*$ is ambiguous in general. Consider, for example,

$$Q_A^U - Q_A^* = \lambda_2 \left[f(e_{1A}^U) - f(e_{1A}^*) \right] + \left[g(e_{2A}^*) - g(e_{2A}^U) \right], \tag{15}$$

[12]Assumption 2(i) is satisfied by a wide class of standard functional forms for $g(e)$. For instance, $g(e) = e^\alpha$ with $\alpha \in (0, 1)$ gives $\eta(e) = e^{2-\alpha}/\alpha$, which is convex; $g(e) = \ln(1+e)$ gives $\eta(e) = e(1+e)$, which is convex; and $g(e) = e/(1+e)$ gives $\eta(e) = e(1 + e)^2$, which is also convex.

[13]This follows from the fact that agents who ignore the negative cross-task spillover effects tend to choose excessive effort on their own assigned task.

where the first term is positive and the second term is negative because U-form induces higher both environmental and economic effort than the social optimum. U-form may therefore not always over-pollute relative to the optimum, because the over-abatement from excess environmental effort can dominate the excess pollution from economic effort.

Our next proposition discusses how M-form deviates from the surplus optimum, where the direction of performance gaps can be signed unambiguously:

Proposition 2 *Suppose Assumption 1 holds. Under M-form, downstream effort choices coincide with the surplus optimum:* $e_{1B}^M = e_{1B}^*$ *and* $e_{2B}^M = e_{2B}^*$*. Upstream economic (environmental) effort is higher (lower) than the surplus optimum:* $e_{1A}^M \geq e_{1A}^*$ *and* $e_{2A}^M \leq e_{2A}^*$*. Consequently, upstream economic performance is weakly higher and environmental performance is weakly worse in both regions relative to the surplus optimum.*

The intuition is straightforward. Since the only externality facing downstream bureaucrats is the cross-task externality, and M-form internalizes precisely this, their effort choices replicate the surplus optimum. Upstream bureaucrats also internalize the cross-task externality, but ignore the pollution outflow $(1-\delta)Q_A$ they impose on the downstream region. This leads to over-investment in economic effort and under-investment in environmental effort upstream, generating excess pollution that flows downstream and worsens environmental performance in both regions.

We have now shown that each organizational form is able to incentivize agents to internalize only one type of environment related externalities. Therefore neither of them is able to achieve the surplus optimum outcome. The following proposition summarizes which organizational form is the second-best structure of the bureaucracy that leads to a better balancing between incentives and internalization of externality. The answer, unsurprisingly, depends on the intensity of different types of externalities:

Proposition 3 *Under Assumption 1, M-form is more likely to deliver higher total surplus than U-form if the spillover from economic task to environmental task* λ_2 *is stronger, and, under Assumption 2, the cross region pollution externality* $1-\delta$ *is weaker.*

Recall that the advantage of M-form organization is better internalization of task specific externality, and the advantage of U-form organization is better internalization of regional pollution externality. Hence it follows that when task specific externality is sufficiently strong and regional pollution externality is less salient, M-form bureaucracy will be more likely to become the second-best organizational form to deliver higher total surplus than U-form.

Note that this result also requires Assumption 2(ii) to hold[14]. A higher δ weakens pollution spillovers and therefore reduces U-form's regional coordination advantage. However, it also induces the U-form to reduce excessive upstream environmental effort, since less pollution is transmitted downstream, which can partially improve its surplus. Assumption 2(ii) ensures that this latter force does not dominate. If the condition failed, the organizational tradeoff would remain, but the comparative static with respect to δ would no longer be globally monotone.

2.2 Extension: Yardstick Competition within M-form

So far, we have examined the simple case in which agents under different organizational forms care only about their own performances in their objective functions. However, a classic argument for the

[14] We can also show that δ^* is non-vacuous given specific functional forms such as $f(e) = \sqrt{e}$ and $g(e) = \xi\sqrt{e}$.

advantage of M-form organization is that it facilitates yardstick competition and thereby incentivizes agents to exert effort (Maskin et al., 2000). This raises a natural question in our setting: can sufficiently intense yardstick competition among agents, who face different externalities, still bring total surplus of bureaucratic tasks under M-form closer to the surplus optimum?

We now present a simple extension of the M-form model where agents care about their performance relative to their upstream or downstream counterparts. I argue that, in the presence of the environment related externalities, yardstick competition may distort effort choices under M-form organization even further away from the surplus optimum, compared to the baseline model where agents are evaluated on their own absolute performances. Higher intensity of competition on the economic and environmental dimension may mitigate or exacerbate this problem.

Consider a top manager who decides which of the two local leaders (i.e., river chiefs) in regions A and B to promote. A local leader receives an exogenous benefit D if promoted and zero otherwise. Leader A will be promoted if and only if

$$Y_A - Q_A + \phi \geq Y_B - Q_B, \tag{16}$$

where ϕ is a preference shock uniform on $\left[-\frac{1}{2\sigma}, \frac{1}{2\sigma}\right]$ with $\sigma \geq 1$. This captures the political factors in promotion decisions, such as political connections or loyalty of local leader A to the top leadership relative to leader B, factional affiliations, relative age[15], and so on. The probability that leader A is promoted is simply[16]

$$\frac{1}{2} + \sigma\left[(Y_A - Q_A) - (Y_B - Q_B)\right], \tag{17}$$

which is increasing in the difference in economic and environmental performance between region A and B. Following a simplified version of the political competition framework in Besley et al. (2010), we interpret a higher σ as reflecting lower salience of political factors, which in turn intensifies competition on economic and environmental dimensions, and increases the weight of economic/environmental performance in promotion decisions. In fact, in the empirical section, I proxy for the salience of political factors using age similarity among local leaders: when river chiefs are of similar age, political considerations may matter relatively less for promotion prospects.

Now, instead of maximizing the overall absolute performance on the two tasks (while considering disutility of effort) as in the previous section, the bureaucrats care about the probability of winning their promotion competition, which in turn translates into the performance difference between the upstream and downstream regions. The upstream river chief will now choose $\{e_{1A}, e_{2A}\}$ to maximize

$$V_A^{MC}(e_{1A}, e_{2A}) = D\sigma\left[(Y_A - Q_A) - (Y_B - Q_B)\right] + \frac{D}{2} - \frac{1}{2}(e_{1A})^2 - \frac{1}{2}\omega(e_{2A})^2, \tag{18}$$

which gives first order conditions:

$$D\sigma(1 - \lambda_2\delta)\, f'(e_{1A}^{MC}) = e_{1A}^{MC}; \tag{19}$$

$$D\sigma(\delta - \lambda_1)\, g'(e_{2A}^{MC}) = \omega\, e_{2A}^{MC}. \tag{20}$$

[15]For example, among leaders at the same administrative level, younger officials may have stronger promotion prospects, while older ones are more likely to be expecting retirement in the near future (Shih et al., 2012).

[16]We adopt this simple promotion rule which depends on the relative performance of the two agents. One can indeed consider a sophisticated top manager who discounts the upstream bureaucrat's performance by the pollution $(1-\delta)Q_A$ it imposes on the downstream. In practice, however, such discounting can be difficult to implement precisely due to information frictions. Monitoring stations are not always located at regional borders, and pollutant dilution is subject to complex hydrological and ecological factors.

The objective function and these first order conditions reveal how relative performance evaluation through yardstick competition distorts agents' incentives. Since a fraction $(1-\delta)$ of upstream pollution flows downstream, the upstream agent can gain a **competitive advantage** by deliberately exploiting the cross-region externality: generating more pollution directly degrades the downstream competitor's environmental performance. As a result, the upstream bureaucrat effectively discounts the pollution it generates, caring only about the δ fraction that remains within its own region, as precisely reflected in the coefficient $(\delta-\lambda_1)$ on environmental effort and $(1-\lambda_2\delta)$ on economic effort in the upstream FOCs, compared to $(1-\lambda_1)$ and $(1-\lambda_2)$ in the baseline M-form. In fact when $\delta < \lambda_1$, the upstream river chief simply sets $e_{2A}^{MC} = 0$, i.e., a corner solution where environmental effort is completely abandoned, since the competitive gain from degrading the downstream region's environment outweighs any local benefit from abatement. To guarantee an interior solution, let us impose

Assumption 3 *$\delta > \lambda_1$.*

The political salience parameter σ further scales these incentives: a higher σ, i.e., more intense performance-based competition, unambiguously raises effort choices for both tasks (provided Assumption 3 holds). The cross-region pollution externality therefore introduces a fundamental asymmetry between the two regions under yardstick competition: upstream incentives are qualitatively distorted by the strategic exploitation of cross-region spillovers, whereas, as we see now, downstream incentives simply replicate the baseline M-form scaled by $D\sigma$. The objective function of the downstream river chief now becomes

$$V_B^{MC}(e_{1B}, e_{2B}) = D\sigma\left[(Y_B - Q_B) - (Y_A - Q_A)\right] + \frac{D}{2} - \frac{1}{2}(e_{1B})^2 - \frac{1}{2}\omega(e_{2B})^2,$$

and the first order conditions are

$$D\sigma(1-\lambda_2)\, f'(e_{1B}^{MC}) = e_{1B}^{MC}; \tag{21}$$

$$D\sigma(1-\lambda_1)\, g'(e_{2B}^{MC}) = \omega e_{2B}^{MC}. \tag{22}$$

For simplicity, let us further normalize $D = 1$. Then the following proposition summarizes the discussion on yardstick competition in M-form:

Proposition 4 *Suppose Assumptions 1 and 3 hold:*

(i) When $\sigma = 1$, the upstream agent under yardstick competition exerts more effort on the economic task and less on the environmental task than both the surplus optimum and the baseline M-form: $e_{1A}^{MC} > e_{1A}^{M} > e_{1A}^{*}$ and $e_{2A}^{MC} < e_{2A}^{M} < e_{2A}^{*}$. The downstream agent's effort choices coincide with the surplus optimum: $e_{1B}^{MC} = e_{1B}^{*}$ and $e_{2B}^{MC} = e_{2B}^{*}$. Consequently, upstream pollution and economic performance both strictly exceed the surplus optimum, $Q_A^{MC} > Q_A^{*}$ and $Y_A^{MC} > Y_A^{*}$, while downstream economic performance coincides with it, $Y_B^{MC} = Y_B^{*}$, and downstream pollution exceeds it solely through upstream spillovers: $Q_B^{MC} - Q_B^{*} = (1-\delta)(Q_A^{MC} - Q_A^{*}) \geq 0$.

(ii) Higher $\sigma > 1$ exacerbates the distortion on the upstream economic effort choice but may at least partially mitigate the distortion on upstream environmental effort choice. The downstream effort choices now strictly exceed the surplus optimum.

The key insight of Proposition 4, as we discussed earlier, is that yardstick competition introduces a strategic motive that is absent in the baseline M-form: because of the asymmetric pollution cross region externality, the upstream chief recognizes that its own pollution outflows degrade its competitor's environmental performance, and therefore has an incentive to exploit this channel rather than internalize it. Furthermore, when $\sigma > 1$, the stakes of the competition rise, amplifying the upstream distortion on the economic margin while partially offsetting it on the environmental margin, but at the cost of now pulling downstream effort away from the surplus optimum as well. It is also useful to note that when $\sigma > 1$, the performance gaps between the M-form under yardstick competition and the surplus optimum become ambiguous. For example, the upstream pollution gap:

$$Q_A^{MC} - Q_A^* = \lambda_2 \left[f\left(e_{1A}^{MC}(\sigma)\right) - f\left(e_{1A}^*\right) \right] + \left[g\left(e_{2A}^*\right) - g\left(e_{2A}^{MC}(\sigma)\right) \right]. \tag{23}$$

With higher σ, the first bracket, i.e., the generation of pollution from higher economic effort, is higher but the second bracket, i.e., the abatement effect, is lower (because higher competition also increases upstream environmental effort as well). Therefore yardstick competition thus generates a fundamental tension: the same mechanism that motivates effort also incentivizes the strategic exploitation of externalities, potentially making the M-form organization perform worse than in the baseline case without relative performance evaluation.

2.3 Theoretical Implications

We conclude this section by deriving the key theoretical implications for which we will later seek empirical support. Specifically, we characterize conditions under which a shift in organizational structure from U-form to M-form is more likely to lead to an improvement in environmental performance (i.e., reduction in pollution). To provide more structure, we take $\omega = 1$ when the water resource officials take over the task of river management under U-form[17], and $\omega = w > 1$ when the local leaders become the river chief and take the river protection task.

Lastly, for the competition parameter σ, we consider the M-form setting where agents cares about their relative (instead of absolute) performance under yardstick competition.

Denote $\Delta Q_r = Q_r^M - Q_r^U$ as the change in pollution levels, we have:

Proposition 5 *Suppose Assumptions 1 and 2 hold. For both regions $r \in \{A, B\}$, a shift from U-form to M-form is more likely to improve environmental quality (reduce pollution), when:*

(i) the river chief faces lower w: $\frac{\partial \Delta Q_r}{\partial w} > 0$;

(ii) spatial pollution externality is weaker (higher δ): $\frac{\partial \Delta Q_r}{\partial \delta} < 0$;

(iii) spillover from economic task to environmental performance is stronger (higher λ_2): $\frac{\partial \Delta Q_r}{\partial \lambda_2} < 0$.

The effect of competition σ on pollution reduction from U-form to M-form is in general ambiguous.

Proposition 5 summarizes different forces that determine when the river chief system is more likely to improve environmental quality. The first concerns the cost of environmental management. Under U-form, river management is delegated to specialized water-resource officials, while under M-form it is assigned to local leaders. Therefore, when river chiefs face a lower cost of environmental effort, M-form is more likely to reduce pollution. Secondly, the effectiveness of the M-form reform also depends on the intensity of the different types of externalities. A higher δ means that upstream pollution dissipates more locally and imposes weaker external costs on downstream regions. This weakens the

[17] See Kong and Liu (2024) for evidence for more environment related working experiences among local environment bureaucrats appointed by the provincial government in China.

main advantage of U-form therefore makes M-form more likely to improve environmental quality. On the other hand, a higher λ_2 means that economic activity generates more pollution. Since M-form makes the same official responsible for both economic development and environmental protection, it is better able to internalize this tradeoff. Hence, the environmental gain from moving to M-form is larger when the pollution consequences of economic activity are stronger.

The role of yardstick competition is ambiguous. Stronger competition increases the importance of relative performance, but it does so on both the economic and environmental dimensions. It may encourage river chiefs to exert greater environmental effort, which improves water quality. At the same time, it may also encourage greater economic effort, which increases pollution. Moreover, because upstream pollution affects downstream performance, competition may give upstream officials an additional strategic incentive to exploit cross-region spillovers. The net effect, as we discussed before, therefore depends on whether the abatement from increasing environmental effort dominates the over-pollution from increasing economic effort. This also makes the effect of competition on pollution reduction a natural open empirical question: competition need not uniformly strengthen the environmental effect of the river chief system, and the effect may also vary across different pollutants, as we will see below, depending on their sensitivity to economic activity versus enforcement effort.

3 Institutional Background and Data

3.1 River Chief System Background

China's manufacturing-driven growth over the past decades has led to severe environmental degradation. In the early 2000s, local government officials were largely preoccupied with regional GDP tournaments as a pathway to promotion, leaving environmental concerns largely ignored (Chien and Hong, 2018). A thematic report by World Bank (2018) on water governance in China reveals that 61.3% of the 5118 groundwater monitoring stations received "poor" or "very poor" ratings for water quality; and 22.9% of major lakes and reservoirs have suffered from eutrophication. Water pollution has caused severe health and ecological problems (World Bank, 2007; He et al., 2016).

3.1.1 River Management Prior to River Chief System

Environmental protection was included as one of the key national goals in the Tenth Five-Year Plan in 2001, but this had limited impact on overall water quality. Local officials often adopted a "polluting thy neighbor" strategy, allowing firms located near administrative boundaries to discharge more pollutants relative to upstream counterparts. In 2006, the central government announced that local officials who missed pollution reduction targets would face immediate removal from office. While this reduced cross-boundary pollution along the specific water quality dimensions targeted by the central government, water quality along non-targeted dimensions, such as heavy metal concentrations, showed no improvement (Kahn et al., 2015).

The main authorities for river governance in China are the Ministry of Water Resources and the Ministry of Ecology and Environment (formerly the Ministry of Environmental Protection), along with their local bureaus. The former manages water resources at the national level, while the latter focuses on pollution control and environmental protection (World Bank, 2018). For major rivers such as the Yangtze and Yellow River, ad hoc inter-regional commissions have long been established under the Ministry of Water Resources to facilitate cross-jurisdictional coordination. At the local level, environmental bureaus issue project permits and enforce compliance through fines and business license suspensions.

A central challenge of this governance structure is the coordination failure between functional ministries and local governments (Cai et al., 2016; World Bank, 2018). Ministries seek to limit industrial activity to protect river quality, while local governments prioritize maintaining large manufacturing bases to sustain growth. Compounding this, local environmental bureaus operate under a "dual leadership" arrangement, formally accountable to both their functional superiors and regional governments (Ouyang et al., 2020). Since local governments exercise stronger *de facto* control over personnel appointments and fiscal resources, these bureaus, who shouldered the primary responsibility for cleaning up the environment, often show leniency toward environmental violations to appease local leaders. This coordination failure is precisely what the RCS was designed to address.

3.1.2 River Chief System

The River Chief System (RCS) was first introduced as a local policy experiment in Wuxi in 2007, in response to a cyanobacterial bloom crisis in Lake Tai. Rather than establishing standalone environment-related agencies, the local government grafted the RCS onto the existing bureaucratic structure: senior local officials, including Party secretaries and government heads, were each assigned, at least *de jure*, primary responsibility for governing a designated river in their jurisdiction. This arrangement was subsequently adopted by a number of cities and provinces, including Jiangsu and Zhejiang. In December 2016, the central government mandated the nationwide rollout of the RCS across all four levels of subnational government, province, city, county, and township, with full implementation required by the end of 2018.

River Chiefs and their Responsibilities Under the RCS, senior provincial leaders serve as river chiefs with responsibility for entire rivers within their province, while officials at lower levels, i.e., city, county, and township, assume chieftainship over river segments within their respective jurisdictions. Within each level, seniority determines assignment: more senior officials are designated chiefs for larger rivers. For instance, the Governor of Henan serves as the provincial-level river chief for the Yellow River, one of China's longest rivers, while vice-governors oversee smaller rivers such as the Huai or Wei River. According to the central government directive (State Council, 2016), river chiefs are responsible for water resource protection, shoreline management, pollution prevention and control, and ecological restoration. In practice, river chiefs from neighboring cities also occasionally conduct joint inspections along shared river segments, coordinating enforcement actions at jurisdictional boundaries; we document the prevalence and geography of such events in Section 4.4.3.

Implementation, Plans and Goals Following the central government's announcement in late 2016, each province formulated its own implementation plan for the RCS, setting targets for pollution reduction and water quality improvement. Lower levels of government followed suit with their own local rollouts. The variation in implementation timing across cities, the administrative level we focus on in this paper, is largely bureaucratic in nature, where city-level adoption timing was mostly determined by when their respective province cascaded the mandate downward. Henan Province, for example, announced in May 2017 its intention to fully establish the RCS by year-end, with water quality targets requiring that over 53% of river quality readings reach "Class III" by 2018, rising to 57% by 2019 and 62% by 2020. At the city level, Kaifeng announced its list of city-level river chiefs in August 2017, followed by Zhoukou in November 2017. These lists were subsequently revised in later years as personnel changed.

Evaluation and Accountability According to State Council (2016), river chiefs' performance in improving water quality constitutes a key criterion for official evaluation and promotion. Surface water quality has been monitored by a national network of stations since the 1990s, with readings published online and updated every four hours[18], making it difficult for local officials to manipulate the data. In 2021, the Ministry of Water Resources formally ranked provincial-level river chiefs on their performance and invited the top ten provincial governments to each nominate one city for a financial award. To facilitate public oversight, government websites regularly update the lists of river chiefs, and information boards erected along riverbanks display the responsible chief's name, jurisdiction, and office contact details.

3.2 Data Description

The empirical section studies the effect of the adoption of River Chief System on water quality outcomes at the city level, using a monthly panel from 2015 to 2020 that merges RCS adoption data manually collected from local government websites, water quality readings from central and provincial monitoring stations, and controls from different sources such as Chinese city statistical yearbooks.

River Chief System Data I manually collect RCS implementation timelines and river chief name lists from local government websites. Figure 2A maps the city-level roll-out: dark purple indicates cities with RCS in place predating the central government's late-2016 nationwide mandate, these are dropped from the analysis[19]. Dark orange indicates the latest adopters (around January 2018). The majority of cities announced RCS implementation and published their river chief lists in 2017. White areas are either centrally administered municipalities or cities for which I could not locate river chief information. The empirical strategy exploits this staggered adoption across cities to identify the dynamic and heterogeneous effects of RCS on water quality.

To assess whether adoption timing is systematically related to pre-existing city characteristics, I classify cities in our dataset into early and late adopters according to whether they implemented RCS before or after the sample median adoption month, and compare their 2015 baseline characteristics[20]. Table A.1 shows that the two groups are broadly balanced across industrial, pollution, and geographic dimensions. Among the city characteristics in Panel B, only log industrial output and the industrial solid-waste utilization rate differ at conventional levels, and neither survives the inclusion of province fixed effects in Table A.2, where we present estimates of a linear probability model regressing early adopter status on city characteristics.

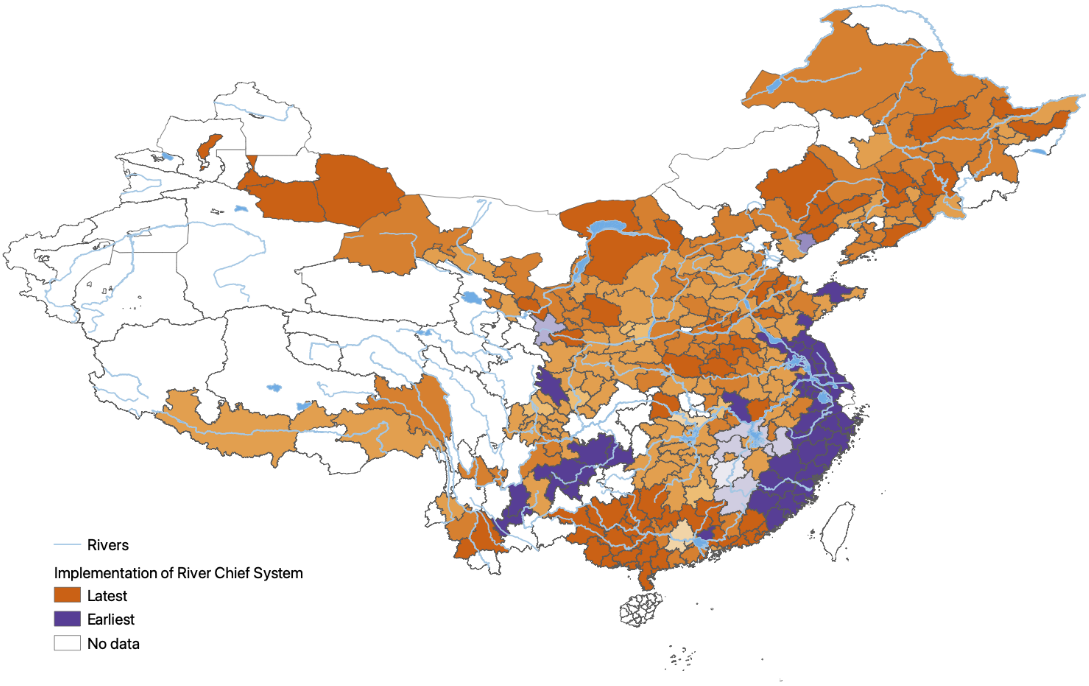
Of particular importance for our identification strategy, adoption timing is uncorrelated with pre-RCS water quality. Panel A of Table A.1 shows that early and late adopters are statistically indistinguishable on baseline dissolved oxygen, ammonia nitrogen, and the composite water-quality index (all $p > 0.16$): it is not the case that more heavily polluted cities adopted RCS marginally earlier. Table A.2 again confirms this. Adding the three pre-treatment water-quality measures in columns 3–4, we find that no characteristic predicts early adoption once province fixed effects are absorbed (Column 4). This is consistent with timing being driven by province-level roll-out schedules rather than by local pollution conditions. Taken together, these patterns support the plausibility of our identifying assumption that the staggered roll-out is at least quasi-random, conditional on location

[18] See http://www.cnemc.cn/sssj/.

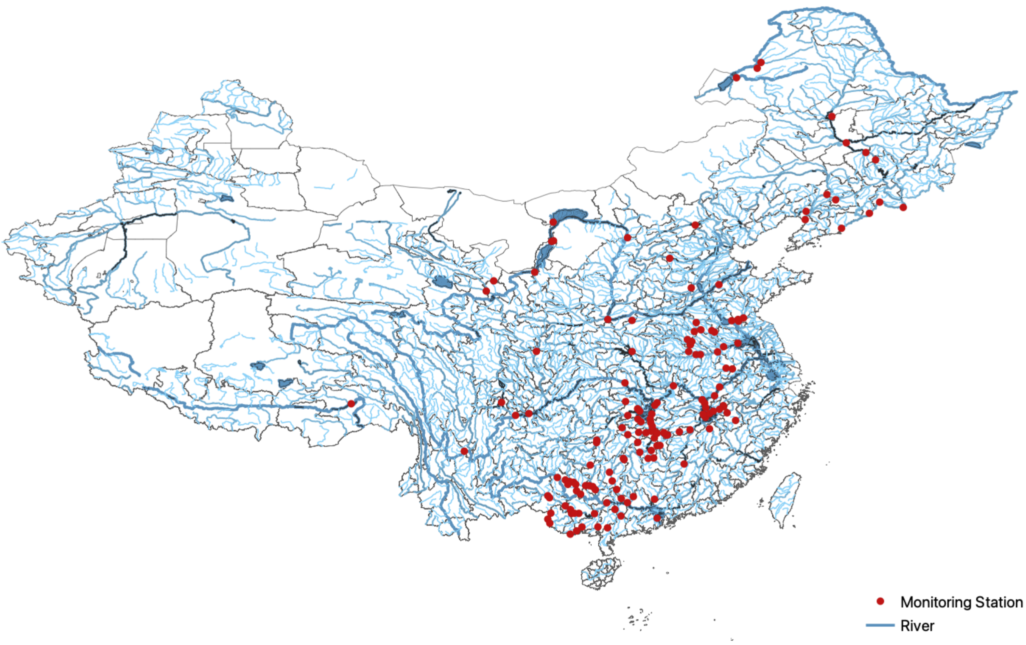
[19] These cities are excluded from our main identifying variation, so including or dropping them does not affect the estimates.

[20] The pre-treatment water-quality comparison (Panel A of Table A.1, and Columns (3)–(4) of Table A.2) is restricted to the 65 cities (34 late, 31 early) with monitoring stations data in 2015; the remaining cities lack a pre-treatment water-quality baseline and therefore do not enter these rows/columns.

Figure 2: River Chief System Implementation and Monitoring Station Distribution



(A) City-Level Roll-Out of RCS



(B) Spatial Distribution of Monitoring Stations

Notes: Panel A maps the city-level timing of RCS adoption. Dark purple indicates cities with RCS in place that predated the central government's late-2016 nationwide mandate and are excluded from the analysis. Dark orange indicates the latest adopters (around January 2018). White areas are either centrally administered municipalities or cities for which river chief information could not be located. Panel B maps the spatial distribution of water quality monitoring stations in the estimation sample, after excluding cities that adopted RCS before 2015. Data on RCS implementation are manually collected from local government websites. Water quality data at the monitoring station level are obtained from EPMAP.

and time fixed effects.

I also collect bureaucratic characteristics from publicly available curriculum vitae. For each city, I cover two key officials: the director of the provincial Water Resources Department (de facto responsible for river management before RCS) and the major river chief, i.e., the party secretary or mayor formally designated as river manager under RCS[21]. Characteristics collected include age, education, and work experiences. As I discuss below, these variables serve as proxies for political competition and the cost of effort for the environmental task, i.e., two key dimensions along which I explore heterogeneous effects of this M-form reform. In addition, I manually collect records of inter-city joint river inspections from local government websites, which capture instances of cross-jurisdictional coordination among river chiefs. I describe the collection procedure in Appendix C.

Water Quality Data I merge RCS information with water quality data from monitoring stations operated across the country. The raw 4-hourly readings are obtained from EPMAP, a Shanghai-based environmental NGO, and averaged to monthly frequency[22]. Figure 2B maps the spatial distribution of monitoring stations in my sample (excluding cities that adopted RCS before 2015). I obtain the geolocation of these monitoring stations from AMap API[23]. Stations are concentrated in the Yangtze and Pearl River basins, the economic heartland of southern China, with the remainder located in northern China, primarily along the Yellow River.

The primary outcomes are three water quality indicators with the highest data coverage and quality in my sample, all measured in mg/L and listed in China's national water quality standard: Dissolved Oxygen (DO), Permanganate Index (COD_{Mn}), and Ammonia Nitrogen (NH_3-N). Higher DO indicates cleaner water, i.e., industrial effluents and sewage consume dissolved oxygen as organic matter degrades, while higher COD_{Mn} and NH_3-N directly reflect contamination from agricultural runoff and industrial chemicals, indicating worse quality. To address multiple inference concerns, I also construct a summary pollution index following Anderson (2012) and Schwab et al. (2020), which applies a generalized least-squares weighting procedure that assigns higher weight to indicators providing independent information. I reverse the sign of DO so that the index increases monotonically with pollution.

Figure 3 plots city-level annual average water quality across the three indicators in 2020,[24] where darker red indicates higher pollution. Water pollution exhibits clear regional concentration. Dissolved oxygen is lowest in southern and northeastern China, where industrial activity is most intensive. High COD_{Mn} and NH_3-N levels are concentrated in central China, which is home to densely populated provinces with heavy reliance on e.g., agriculture.

Additional Data and Summary To explore the heterogeneous effects of the adoption of RCS, I supplement the dataset with city-level characteristics from sources such as Chinese City Statistical Yearbook and National Earth System Science Data Center. Table 1 presents summary statistics for the main variables. Among the water quality outcomes, COD_{Mn} has more missing values than DO and NH_3-N, and NH_3-N is lower in levels and less dispersed than the other two indicators; comparisons across measures should therefore be interpreted with care. As a result, in our empirical estimates, the treatment effects on COD_{Mn} are usually less informative than the other two indicators. Among river

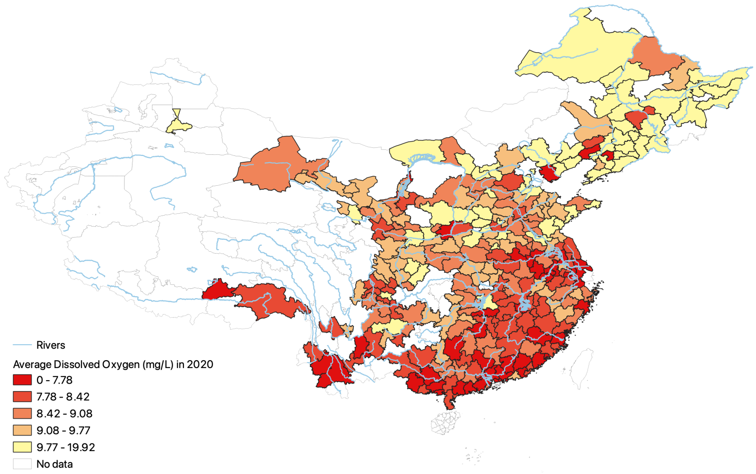
[21] I focus on the single senior river chief responsible for either the largest river in the region or overseeing all lower-level river chiefs, who are typically vice-mayors.

[22] Monthly averaging ensures consistency with the river chief information, which is collected (and updated) at the monthly level.

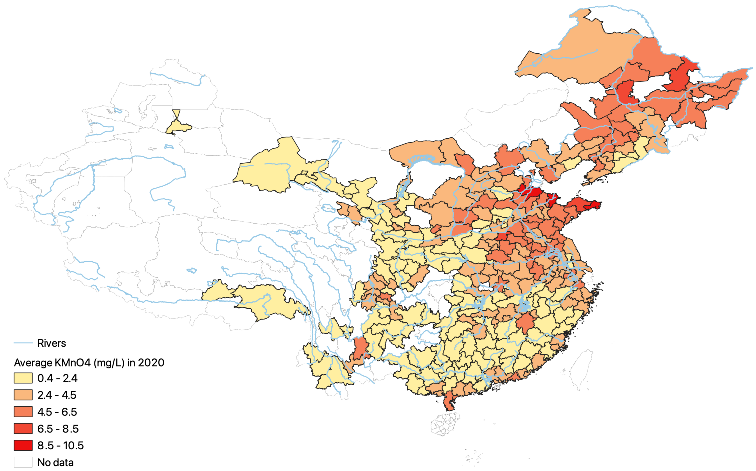
[23] See https://lbs.amap.com/tools/picker.

[24] The 2020 sample contains more monitoring stations and hence more observations than earlier years, providing broader spatial coverage.

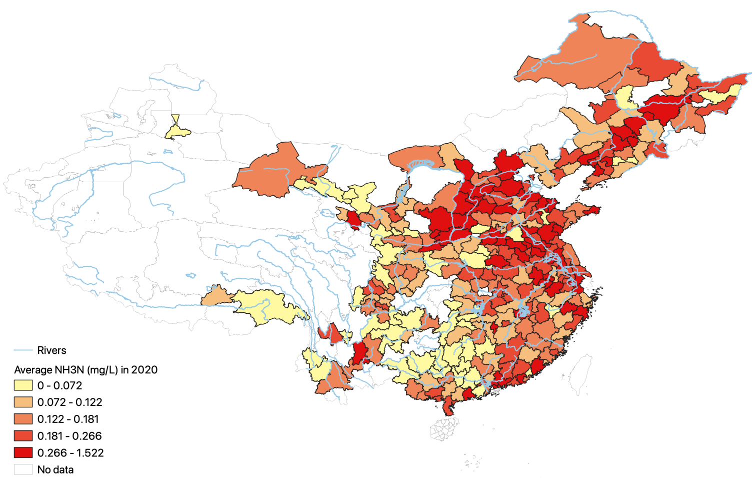
Figure 3: Spatial Distribution of Water Pollution in 2020



(A) Dissolved Oxygen (DO)



(B) Permanganate Index (COD_{Mn})



(C) Ammonia Nitrogen (NH_3-N)

Notes: This figure maps city-level annual average water quality across three indicators in 2020. Darker red indicates higher pollution (lower dissolved oxygen in Panel A; higher concentrations of COD_{Mn} and NH_3-N in Panels B and C). All indicators are measured in mg/L. Data are obtained from EPMAP.

Table 1: Summary Statistics

	Obs.	Mean	Std. Dev.	Min	Max
Panel A: Water Quality Variables					
Dissolved Oxygen (mg/L)	13,166	7.833	2.254	0.215	15.240
Permanganate Index, COD_{Mn} (mg/L)	10,298	3.356	1.810	0.080	12.477
Ammonia Nitrogen, NH_3-N (mg/L)	12,067	0.330	0.361	0.000	2.793
Panel B: City Characteristics					
Service share of city GDP (%)	542	45.841	7.570	25.170	68.040
Industrial wastewater discharge (10,000 tonnes)	487	5,622.8	6,653.7	3.000	60,506
Average land slope	109	12.283	5.431	2.631	30.573
Panel C: River Chief Characteristics					
Age	214	52.014	3.133	43	60
High education (binary)	214	0.364	0.482	0	1

Notes: Panel A reports summary statistics at the monitoring station×month level. Dissolved oxygen, permanganate index, and ammonia nitrogen are obtained from EPMAP. Panel B reports city-level characteristics over 2015–2020, drawn from the Chinese City Statistical Yearbook. Average land slope is a time-invariant geographic variable calculated from the National Earth System Science Data Center. Panel C reports characteristics of major river chiefs collected from publicly available curriculum vitae. High education is a binary variable equal to one if the river chief holds a full-time master's or PhD degree (part-time master's degrees excluded), and zero otherwise. Cities that adopted RCS before 2015 are excluded from all panels.

chief characteristics, the mean age is 52, with a range of 43 to 60. Some 36.4% of river chiefs hold a full-time master's or PhD degree. Both land slope and service sector share, which are key proxies for the intensity of externalities that underpin our heterogeneity analysis, exhibit substantial cross-city variation, reflecting the geographic and economic diversity of cities in the sample.

To further explore the mechanisms and conduct robustness checks, I draw on several additional data sources. First, I construct a river sinuosity index using river shapefiles[25], which I combine with average land slope as a joint measure of cross-regional pollution externalities in robustness checks. Second, I obtain city-level counts of active underground wastewater treatment plants from Zhou et al. (2024) to examine whether RCS induced tangible government investment in water infrastructure. Third, I obtain daily air quality data from the CASEarth Data Center, aggregated to monthly frequency, to test whether improvements in river quality spill over into air quality, i.e., a plausible channel if RCS enforcement leads to the reduction of heavy industrial activity which simultaneously generates both water and air pollution.

4 Empirical Evidence

4.1 Empirical Strategies

Proxies and Predictions Before presenting the empirical results, I first explain how the key parameters from the theoretical framework in Section 2.3 map onto empirical proxies and translate into testable predictions. Recall that from Proposition 5, the effectiveness of M-form reform in improving environmental outcomes depends on four parameters: the river chief's cost of effort (w), the intensity of spatial pollution externalities (δ), the intensity of task spillovers (λ_2), and the degree of political competition (σ).

Firstly, we can proxy w by a binary variable Education$_c$, equal to one if city c was ever led by

[25]For each river segment, sinuosity is defined as the ratio of the segment's actual length to the straight-line distance between its two endpoints. I retain only segments that cross at least two city boundaries, capturing rivers that connect upstream and downstream jurisdictions, and aggregate to the city level using a length-weighted average across all such segments.

a river chief holding at least a full-time master's or PhD degree during the period when RCS was in place. The intuition is straightforward: a more educated river chief faces a lower cost of effort in the specialized domain of environmental management, and is therefore more likely to exert the effort required to improve river quality.

Secondly, we proxy the intensity of spatial pollution externalities δ by average city land slope. Flatter terrain slows river flow, increasing the likelihood that pollutants sediment locally rather than being carried downstream[26]. Higher slope therefore implies more salient cross-regional externalities, i.e., lower δ in the model. I construct a binary variable $\text{Slope}_c = 1$ if city c is above the median land slope across all cities in the sample.

While land slope captures the speed of river flow, it may not fully characterize the geometry of river channels which can also affect the sedimentation of pollutants[27]. I therefore also construct a river sinuosity index, measuring the ratio of actual river length to straight-line distance for cross-city river segments, which captures a complementary dimension of pollution transport: more sinuous rivers provide greater opportunity for pollutants to sediment before reaching downstream jurisdictions. In the robustness checks, we will combine slope and sinuosity into a composite index to obtain an alternative measure of cross-regional pollution externality intensity, and show that the heterogeneity results are robust to this alternative proxy.

Thirdly, we proxy the intensity of the spillover of economic task to environmental performance λ_2 by the service sector share of local GDP. The key observation is that our three river quality indicators primarily capture agricultural and industrial pollution. A bureaucrat tasked with promoting a service-oriented economy therefore faces weaker spillovers to environmental outcomes, since service sector activity generates relatively less water pollution. By contrast, promoting an economy heavily reliant on polluting industries is more environmentally costly, and it is precisely in such cities, according to Proposition 5, that M-form organization may deliver the greatest improvement in environmental outcomes relative to U-form. I construct a binary variable $\text{ServiceShare}_c = 1$ if city c's average service share of GDP over 2015–2016 (before the national rollout of RCS) exceeds the national median.

As a robustness check, we can also construct an alternative proxy for task spillover intensity: the ratio of industrial wastewater discharge to gross industrial output value (i.e., wastewater intensity of industrial production) in the pre-treatment period. Cities with higher wastewater intensity have dirtier industrial production, implying stronger spillovers between economic promotion and environmental outcomes, and should therefore exhibit larger treatment effects of RCS adoption.

Finally, we proxy the level of political competition σ using within-province variation in river chiefs' ages. City leaders compete for promotion to provincial or ministerial positions, and age is a crucial determinant of promotion prospects: informal age thresholds in China's cadre system favor younger officials, who therefore have stronger incentives to perform well across all bureaucratic tasks (Xu, 2011; Wang et al., 2020; Shih et al., 2012). Within a province, high age dispersion implies that younger officials already enjoy a structural advantage on the age dimension while their older counterparts face imminent retirement, therefore reducing the intensity of head-to-head competition. Conversely, when city leaders within a province are of similar age, they are closer substitutes as promotion candidates, and competition on performance dimensions such as environmental and economic outcomes becomes more intense.

To operationalize this, I compute the standard deviation of river chiefs' ages within each province-

[26] See Brunke and Gonser (1997) on how high transport capacity and erosional activity in steep gorge streams produce unstable sediments.

[27] See Xiao et al. (2020) for the relationship between river sinuosity and its self-purification capacity.

year, restricting to cities where RCS is already in place (since these officials are the relevant competitors for provincial leaders making promotion decisions).[28] I then classify a province-year as high competition if its age standard deviation falls below the median across all provinces in the sample, and construct a binary variable $\text{Competition}_c = 1$ if city c was ever located in a high-competition province during the years when RCS is in place.

With these empirical proxies in mind[29], Proposition 5 therefore translates into the following empirical predictions:

Prediction 1 *The effect of RCS adoption on river quality is heterogeneous across cities. Specifically, river quality improvement is more likely to be observed:*

(i) in cities led by a river chief with higher educational attainment;

(ii) in cities with below-median land slope;

(iii) in cities with below-median service sector share of GDP;

The effect of competition, measured by within-province river chiefs age dispersion, on river quality improvement is ambiguous.

Event Study Specification To estimate the average effect of RCS adoption on river quality, we have the following main event study specification:

$$y_{mct} = \sum_{h=-\tau}^{T} \beta_h \mathbf{1}\left[D_{ct} = h\right] + \lambda_m + \gamma_t + \varepsilon_{mct}, \tag{24}$$

where y_{mct} is the water quality outcome (or pollution index) of monitoring station m in city c at time t; λ_m and γ_t are monitoring station and time fixed effects; and $\mathbf{1}[D_{ct} = h]$ is an indicator for the h-th period relative to RCS adoption, where $D_{ct} = t - A_c$ and A_c denotes the calendar month in which RCS was first introduced in city c. Given the staggered adoption design and the theoretical prediction of heterogeneous treatment effects, I estimate equation (24) using three recent staggered difference-in-differences estimators robust to treatment effect heterogeneity proposed by de Chaisemartin and D'Haultfœuille (2020), Callaway and Sant'Anna (2021), and Borusyak et al. (2024).

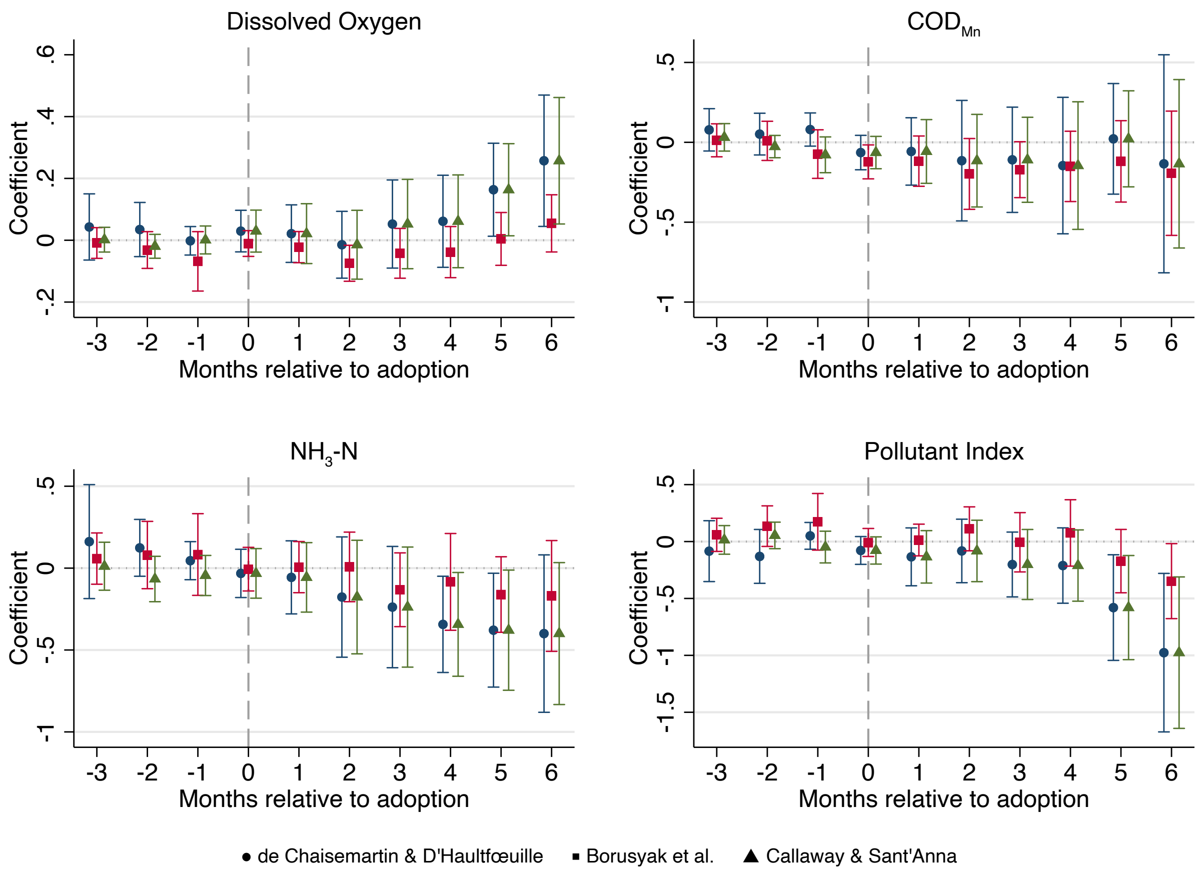
Furthermore, to examine the potential heterogeneous treatment effects, we will estimate equation (24) but separately for cities on either side of each binary partition, i.e., $\text{Education}_c \in \{0,1\}$, $\text{Slope}_c \in \{0,1\}$, $\text{ServiceShare}_c \in \{0,1\}$, and $\text{Competition}_c \in \{0,1\}$, and compare the estimated treatment effects across groups.

The remainder of this section proceeds as follows. We will first present estimates of the average effect of RCS adoption on river quality, then examine heterogeneity through the lens of the four predictions derived above. We subsequently present a series of robustness checks and additional results: we address potential spatial spillover concerns by constructing a spatially thinned subsample of monitoring stations where we remove the spillover control stations; we then verify robustness to alternative measures of the heterogeneity proxies; and we provide evidence on potential mechanisms, i.e., whether RCS induced investment in underground wastewater treatment infrastructure, and whether improvements in river quality spilled over into air quality, etc.

[28] This measure varies over time due to the rotation of city leaders; see Jia and Xu (2020).

[29] One might worry that these four proxies capture some unified underlying factors, such as local economic development, rather than the four distinct channels of the theory. Appendix Table A.3 reports the correlations of our main proxy variables and suggests otherwise. Education is essentially uncorrelated with the other three proxies (all $|\rho| < 0.13$), and slope and service share overlap only weakly ($\rho = -0.31$), with the only sizeable correlation between competition and slope ($\rho = -0.69$). The proxies thus partition cities along largely distinct dimensions; hence this strengthens our confidence that the different dimensions of heterogeneous effects we document are not driven by a single common factor.

Figure 4: Average Effect of RCS Adoption



Notes: This figure plots event study estimates of the average effect of RCS adoption on river quality across four outcomes, namely, Dissolved Oxygen, COD_{Mn}, NH_3-N, and the pollutant index, estimated using equation (24). The first three outcome variables are taken logarithm. The horizontal axis denotes months relative to RCS adoption. Results are reported for three staggered difference-in-differences estimators: de Chaisemartin and D'Haultføeuille (2020) (circles), Borusyak et al. (2024) (squares), and Callaway and Sant'Anna (2021) (triangles). The sample spans January 2015 to December 2020, excluding cities that adopted RCS before 2015. All specifications include monitoring station and time fixed effects. Confidence intervals are at the 95% level.

4.2 Core Results

With the empirical proxies and specification in place, I now present the results.

4.2.1 Average Effects

Figure 4 presents estimates of equation (24), i.e, the average effect of RCS adoption on the four river quality outcomes. Several findings stand out. Firstly, pre-trend coefficients are consistently close to zero and statistically insignificant across outcomes and estimators, supporting the identifying assumption that adoption timing is at least quasi-random conditional on station and time fixed effects. Secondly, following RCS adoption, dissolved oxygen levels increase and ammonia nitrogen declines, providing consistent evidence that RCS is taking effect in reducing river pollution. The permanganate index, however, shows a weaker and statistically insignificant response[30]. Thirdly, the treatment effects emerge gradually over time, suggesting that the institutional changes induced by RCS take several months to translate into measurable environmental improvements. This is consistent with river chiefs requiring time to mobilize enforcement actions and coordinate with local firms

[30] At least part of the reason is that the COD_{Mn} data in our sample has more missing values.

and bureaucracy. Dissolved oxygen begins to rise from the third month post-adoption, statistically significant reductions in ammonia nitrogen appear from the fourth month, and the composite pollution index begins to fall from the fifth month. By six months post-adoption, dissolved oxygen has increased by approximately 20% and ammonia nitrogen has declined by approximately 30%, with the composite pollution index falling by around 0.3-1 standard deviations. The three estimators, i.e., de Chaisemartin and D'Haultfœuille (2020), Borusyak et al. (2024), and Callaway and Sant'Anna (2021), yield broadly consistent point estimates throughout, lending confidence to the robustness of these findings[31]. One thing to note is that the event window is necessarily limited to six months post-adoption: beyond this, the roll-out of RCS is largely complete across cities in the sample, leaving insufficient variation to support reliable estimation.

These average effects paint an encouraging picture of the effectiveness of M-form reform. However, they may obscure important heterogeneity: as the theory highlights, the effectiveness of M-form organization in addressing environmental problems is inherently context-specific, depending on the cost of effort, the intensity of pollution externalities, task spillovers, and the degree of political competition. We now turn to these potential dimensions of heterogeneous impacts.

4.2.2 Heterogeneous Effects

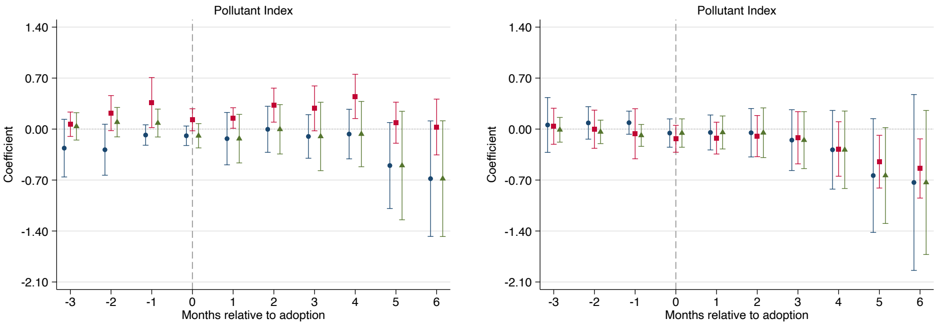
We now turn to the heterogeneous effects of RCS adoption, focusing on the composite pollution index as the primary outcome. Results for the three individual water quality indicators are reported in Appendix Figure A.1, A.2, A.3, and A.4.

River Chief Education Panel (A) of Figure 5 presents the heterogeneous effects by river chief educational attainment. For cities led by a river chief with at least a full-time master's or PhD degree, the pollution index shows reduction effects from the fourth month post-adoption, with point estimates reaching approximately 0.7 standard deviations by the sixth month according to the Callaway and Sant'Anna (2021) and de Chaisemartin and D'Haultfœuille (2020) estimators. In contrast, cities whose river chiefs do not meet this educational threshold have coefficients lower in magnitude throughout the time periods post-adoption. We interpret this pattern as indicative evidence in support of Prediction (i): the effectiveness of M-form reform in improving environmental outcomes is greater when the designated river chief possesses higher educational attainment. Environmental management is a knowledge-intensive task, hence a more educated river chief has greater capacity to acquire and apply the specialized knowledge required to design and enforce effective pollution control measures, thereby facing a lower cost of effort w in the model. This finding resonates with a broader literature documenting that leader quality shapes policy outcomes (Besley et al., 2011), though our result is more specific: it emphasizes the role in reducing the cost of a technically demanding task that drives the heterogeneity of M-form reform.

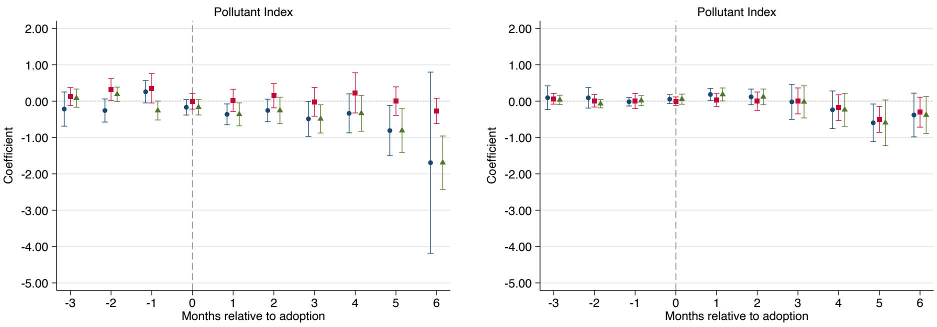
Land Slope Panel (B) reports the heterogeneous effects by median land slope. For cities below the median land slope, which according to our proxy face weaker cross-regional pollution externalities, the pollution index begins to decline significantly from the fifth month. By the sixth month, there is an around 1.6 standard deviations reduction of the pollution index according to the de Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021) estimators. For cities above the median slope, the treatment effect is more muted: the pollution index shows a modest decline only

[31] In our analysis, the Borusyak et al. (2024) estimator often produces smaller magnitudes than the other two estimators, and the gap in magnitude is larger in later post-adoption periods. This could be attributed to the fact that our RCS adoption becomes nearly universal across cities, and how the different estimators construct untreated counterfactuals.

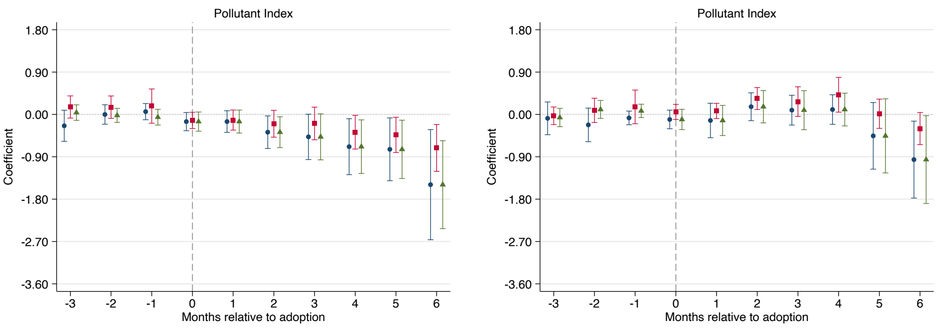
Figure 5: Heterogeneous Effects of RCS Adoption on Pollution Index



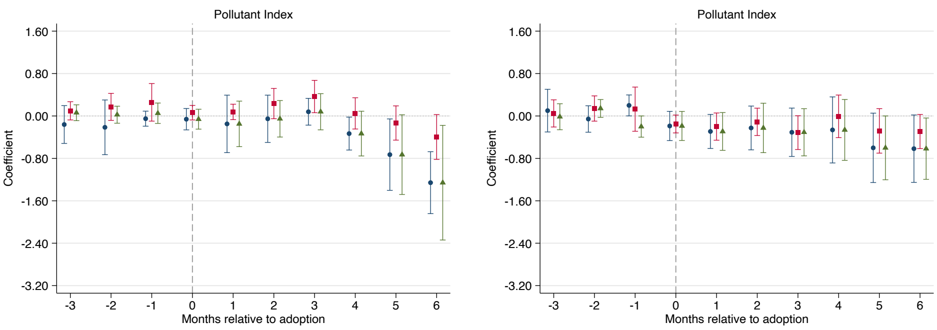
(A) Below (left) and above (right) master's degree



(B) Below (left) and above (right) median land slope



(C) Below (left) and above (right) median service sector share of GDP



(D) Low (left) and high (right) political competition

Notes: This figure plots estimates of the heterogeneous effect of RCS adoption on the pollution index. Panel (A) splits cities by river chief educational attainment (below vs above master's degree). Panel (B) splits cities by median land slope. Panel (C) splits cities by median service sector share of GDP. Panel (D) splits cities by the degree of political competition. The horizontal axis denotes months relative to RCS adoption. Results are reported for three staggered difference-in-differences estimators: de Chaisemartin and D'Haultfœuille (2020) (circles), Borusyak et al. (2024) (squares), and Callaway and Sant'Anna (2021) (triangles). The sample spans January 2015 to December 2020, excluding cities that adopted RCS before 2015. All specifications include monitoring station and time fixed effects. Confidence intervals are at the 95% level.

in the later months of the post-adoption window, and the point estimates are considerably smaller in magnitude. This pattern is consistent with Prediction (ii). Under M-form organization, river chiefs are not incentivized to internalize cross-regional pollution externalities; this is precisely the organizational disadvantage that U-form, through its functional specialization of water resource officials, is better placed to address. The shift to M-form is therefore more likely to deliver environmental improvements in cities where such cross-regional externalities are less salient, i.e., where flatter terrain slows river flow and allows pollutants to sediment locally rather than being carried downstream.

Service Sector Share Panel (C) examines heterogeneity by the service sector share of local GDP. Cities below the median service share, which are more reliant on polluting industrial and agricultural activity and therefore face stronger spillovers from economic promotion to environmental outcomes, exhibit larger treatment effects. The pollution index begins to decline significantly as early as the third month post-adoption for this group, and by the sixth month the reduction reaches approximately 1.3 standard deviations according to the de Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021) estimators. Among cities above the median service share, we only observe a statistically significant decline in the pollution index at the sixth month. This result is again in line with the context-specificity of M-form reform and Prediction (iii). Since the main advantage of M-form organization in the presence of environmental externalities is the better internalization of the tradeoff between economic and environmental tasks, the shift to M-form is most effective in cities where this economy-environment conflict is most salient: those where economic activity generates more pollution, and where a single official accountable for both objectives is best placed to manage this tension.

Political Competition Panel (D) presents the heterogeneous effects by political competition intensity, proxied by within-province age dispersion among river chiefs. The results are informative precisely because the theory yields no sharp directional prediction on this dimension. Among cities in low-competition provinces, we start to see pollution reduction effect in the fifth month; then by the sixth month, the de Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021) estimators point to a reduction of approximately 1.2 standard deviations. In high-competition provinces, the pollution index also declines by the sixth month, with estimates of approximately 0.5 standard deviations across estimators. On the composite pollution index, therefore, low-competition cities exhibit relatively larger reductions, suggesting that higher competition among political agents may not always improve performances, and the strategic exploitation of cross-regional externalities under more intense yardstick competition may at least partially offset the gains from M-form reform.

However, this aggregate picture conceals important heterogeneity across individual pollutants that may shed light on the underlying mechanism. Figure A.4 disaggregates the treatment effects by competition for each of the three water quality indicators separately, with the right column corresponding to high-competition cities and the left column to low-competition cities. Two patterns stand out. First, for dissolved oxygen, high-competition cities exhibit a clear and statistically significant improvement, with DO rising by approximately 0.3 log points by the sixth month, while low-competition cities show improvement in DO with lower magnitude. Second, for ammonia nitrogen, the pattern reverses: low-competition cities exhibit significant reductions in NH_3-N of around 0.4–0.5 log points by the sixth month, whereas high-competition cities show less decline. The effects on COD_{Mn} are more noisy and less informative across both groups.

To interpret such discrepancy across pollutant measures, recall from Proposition 4 and Proposition 5 that theoretically the sign of the competition effect depends on whether the abatement gains from increased environmental effort dominate the over-pollution of increased economic effort. In fact, in the Appendix Proof for Proposition 5, we also give an example with specific functional forms to demonstrate that when the environmental effort is sufficiently effective, higher competition under M-form is conducive to pollution reduction. Now turning to the empirics, notice first that dissolved oxygen is primarily depleted by industrial effluents and domestic sewage, for which enforcement-based abatement can be highly effective; hence the abatement gains are more likely to dominate the over-pollution effect. On the other hand, ammonia nitrogen largely reflects agricultural runoff such as the use of agricultural fertilizers (Gao et al., 2022), which is more diffuse and harder to abate through enforcement actions within a short period of time; hence the over-pollution channel from competition may dominate, and a lower level of competition may be desirable for the M-form reform to reduce pollution. Notably, across the other three heterogeneity dimensions, the comparisons of treatment effects are largely consistent across different pollutant indicators. Hence such pollutant-specific results here can be specifically tied to how competition shapes the incentive to prioritize environmental over economic performances.

We further complement our event-study results with average treatment effect estimates by the proxy variable groups in Appendix Table A.4. The goal is to be more explicit about the differences in treatment effects across groups. We compute the group-specific average treatment effects using the Callaway and Sant'Anna (2021) estimator and report their difference. The average treatment effects estimates are largely consistent with the event study diagrams: for example, we find that the pollutant reduction effect is concentrated entirely among low-slope cities (a Callaway and Sant'Anna (2021) ATT of -0.588 versus a -0.126 for high-slope cities, which translate into a difference of 0.462). The service-share results are similar, with the pollution reduction effect driven by below-median-service cities; and cities with a postgraduate river chief see a somewhat larger reduction effect. However, we do not find large difference of average treatment effect estimates for high and low competition cities[32].

So far, we have documented average and heterogeneous effects of RCS adoption. On average, the reform improves river quality nationwide. But we also find that pollution reduction is more pronounced when the river chief is more educated, cities are located in flatter terrain, and local economies rely more heavily on industrial and agricultural activity. The effect of political competition varies across pollutant measures, consistent with the theoretical ambiguity in Proposition 5. Taken together, these empirical results support our theoretical argument that the effectiveness of M-form reform depends on the relative intensities of the cross-task and cross-regional externalities. We now demonstrate the robustness of these findings with additional empirical exercises.

4.3 Robustness Checks

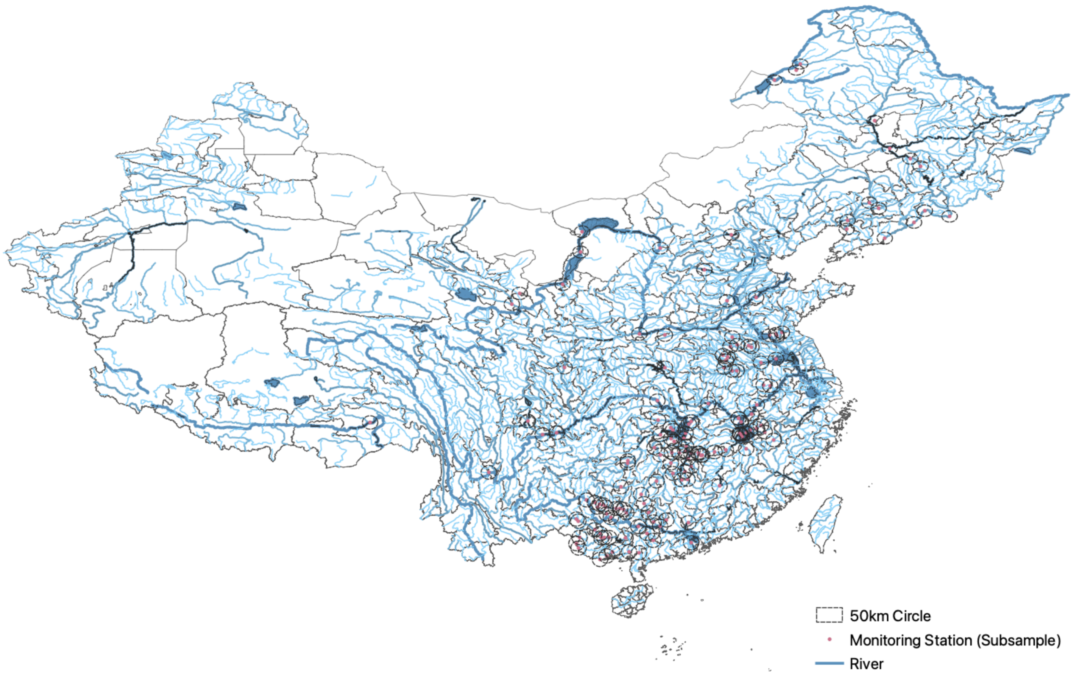
Spatial Spillovers The gradual rollout of RCS enables us to apply staggered difference-in-differences methods to identify its average and heterogeneous effects on river quality. A key concern with this approach, however, is the potential for spatial pollution spillovers: as pollutants flow from upstream to downstream cities along the river, the adoption of RCS in an upstream city may affect water quality in downstream cities that have not yet implemented the reform, thereby violating the stable unit treatment value assumption (SUTVA) and potentially biasing the DiD estimates.

To address this concern, I construct a spatially thinned subsample of monitoring stations for which spillover-induced SUTVA violations are less likely[33]. I draw a 50-kilometer radius around each

[32] Notice that in Panel D of Figure 5, high-competition cities exhibit pollution reductions earlier in the post-adoption window, whereas low-competition cities show larger reductions that emerge later. Averaging over the event window, we find the difference in average treatment effects to be largely muted.

[33] In principle, one could address the spillover concern more directly by constructing an explicit river-network expo-

Figure 6: Spatial Distribution of Monitoring Stations in Thinned Subsample



Notes: This figure maps the spatial distribution of monitoring stations in the spatially thinned subsample. The subsample is constructed by drawing a 50-kilometer radius around each monitoring station, identifying all pairs of stations belonging to different cities but the same river, and randomly dropping one station from each such pair.

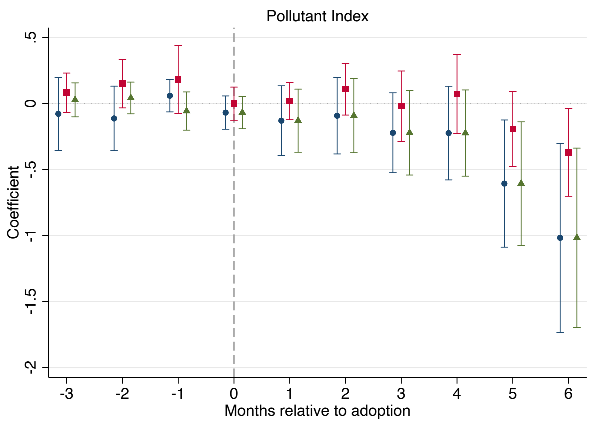
monitoring station,[34] which identifies all pairs of stations within that distance. I then retain only those pairs where both stations belong to different cities, since the treatment unit is at the city level, and to the same river, since pollutants are unlikely to affect water quality across parallel river systems. These are the pairs for which spatial spillovers may plausibly bias the DiD estimates. For each such pair, I randomly drop one station, yielding a spatially thinned subsample on which I re-estimate the average and heterogeneous effects of RCS adoption. Note that monitoring stations in the original dataset are already relatively sparsely distributed across the country, which limits the scope for spillover-induced bias in the main estimates. Figure 6 shows the spatial distribution of the retained stations in this subsample.

Panel (A) of Figure 7 re-estimates the event study specification (24) for the average effect of RCS adoption on the pollution index using the subsample. The results are broadly similar to the full-sample estimates. We again observe a sizable reduction in the pollution index by the fifth and sixth months post-adoption: by the sixth month, the Borusyak et al. (2024) estimator points to a reduction of approximately 0.3 standard deviations, while the de Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021) estimators yield larger estimates (over 1 standard deviation

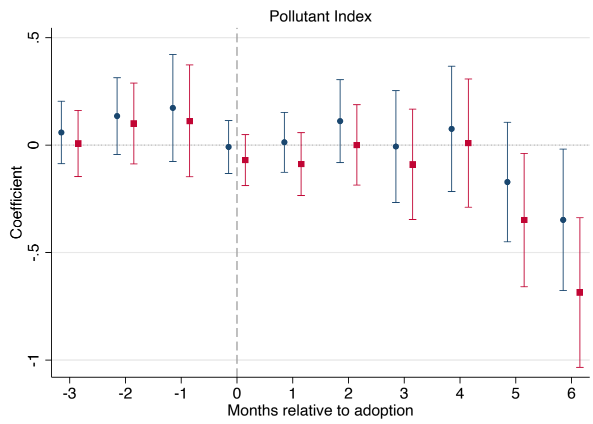
sure measure for each monitoring station: for instance, a distance-weighted index of RCS adoption among upstream jurisdictions. Then one could separately estimate direct local effects from downstream spillovers. For now we are not able to pursue this for two reasons. First, it requires complete information on the RCS adoption status and timing of *all* upstream cities, whereas we observe adoption only for cities in our sample. Second, the monitoring stations in our data are themselves only a sample of the network, so the upstream set of any given station is largely unobserved. Given the already-sparse station network, we therefore construct the spatially thinned subsample as a transparent alternative that removes the control station pairs most likely to violate SUTVA, without modeling the full exposure network.

[34]Water pollutants typically dilute within 5–10 kilometers along a river; see Hashemi Monfared et al. (2017) for a simulation of pollutant transport. Since dilution distances vary with water velocity, land slope, and other hydrological factors, I adopt 50 kilometers as a conservative benchmark.

Figure 7: Robustness Checks: Spatial Thinning and Bureaucrat Fixed Effects



(A) Spatially Thinned Subsample



(B) Bureaucrat Fixed Effects

Notes: Panel (A) plots event study estimates of the effect of RCS adoption on the pollution index using the spatially thinned subsample of monitoring stations. Results in Panel (A) are reported for three staggered difference-in-differences estimators: de Chaisemartin and D'Haultfœuille (2020) (circles), Borusyak et al. (2024) (squares), and Callaway and Sant'Anna (2021) (triangles). Panel (B) plots estimates from the Borusyak et al. (2024) imputation estimator, comparing the benchmark specification (without bureaucrat fixed effects), i.e., the blue circles, against specifications that additionally control for fixed effects of the river chief (i.e., the designated city leader) and the director of the provincial Water Resources Department, i.e., the red squares. The outcome variable is the pollution index in both panels. The horizontal axis denotes months relative to RCS adoption. The sample spans January 2015 to December 2020, excluding cities that adopted RCS before 2015. All specifications include monitoring station and time fixed effects. Confidence intervals are at the 95% level.

reduction). Notably, the treatment effects in this subsample are modestly larger in magnitude than those obtained using the full sample in Figure 4. This is consistent with the direction of bias one would expect in the presence of spatial pollution spillovers: when RCS adoption in an upstream treated city reduces pollution outflows, downstream control cities experience improved water quality as a result, compressing the treated-control difference and leading to an under-estimate of the true treatment effect in the full sample. However, the magnitude of this discrepancy is not large, suggesting that spatial spillovers do not severely contaminate the main estimates, but the direction of the difference confirms that cross-city pollution flows play a role in shaping the measured effect of RCS on river quality.

We replicate the heterogeneity analysis on this subsample and report the results in Appendix Figure A.5. Compared to the benchmark estimates in Figure 5, we also find modestly larger treatment effect estimates throughout the four dimensions of heterogeneity analysis, again consistent with the direction of bias from spatial spillovers. Interestingly, this is especially pronounced among the groups of cities that theory predicts to benefit most from RCS adoption.

Bureaucrats Fixed Effects Another potential concern with the baseline estimates is that RCS adoption may coincide with changes in bureaucratic personnel, and the estimated treatment effect may therefore partly capture the effect of having a different bureaucrat in charge of river management, rather than the organizational form change per se. To address this, we re-estimate the event study specification (24) using the Borusyak et al. (2024) imputation estimator, augmented with fixed effects for both the city leader (who becomes the de facto river chief post-adoption) and the director of the provincial Water Resources Department (who was the de facto river manager pre-adoption). Crucially, we include these fixed effects for the entire sample period, regardless of which bureaucrat is formally responsible for river management at any given time. This ensures that the treatment effect identifies the impact of the *de jure* organizational form change itself, holding the bureaucratic personnel fixed.

Panel (B) of Figure 7 presents the results. The blue circles reproduce the benchmark estimates without bureaucrat fixed effects, and the red squares show the estimates augmented with such fixed effects. Adding bureaucrat fixed effects yields treatment effect estimates that are slightly larger in magnitude than the benchmark. This tends to suggest that, if anything, cities that happened to receive a less effective bureaucrat at the time of RCS adoption would otherwise dampen the estimated treatment effect. Controlling for such personnel differences thus reveals a stronger underlying effect of the organizational form change itself.

Alternative Proxies for Externality Intensity We now consider alternative proxies for externality intensity, with results presented in Figure 8. As mentioned earlier, for the spatial pollution externality, we construct a composite index combining average land slope and river sinuosity for each city, which capture complementary dimensions of pollutant transport: slope governs the speed of river flow, while sinuosity determines the opportunity for pollutants to sediment before reaching downstream jurisdictions. Panel (A) splits cities by the median of this composite index. Cities below the median, facing weaker cross-regional externalities, exhibit a reduction in the pollution index of around 1.3 standard deviations by the sixth month according to the de Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021) estimators whereas the Borusyak et al. (2024) estimator yields a reduction of 0.4 standard deviation. Among cities above the median, we observe a temporary reduction effect in the fifth month but the coefficient reverts back to zero in the sixth month.

Panel (B) turns to an alternative proxy for task spillover intensity: the ratio of industrial wastewater discharge to gross industrial output value in the pre-treatment period. Among cities above the median wastewater intensity, all three estimators point to a large and statistically significant reduction in the pollution index by the sixth month. Among cities below the median, the treatment effect is smaller in magnitude. Importantly, both results are consistent with our earlier heterogeneity analysis using land slope and service sector share of GDP.

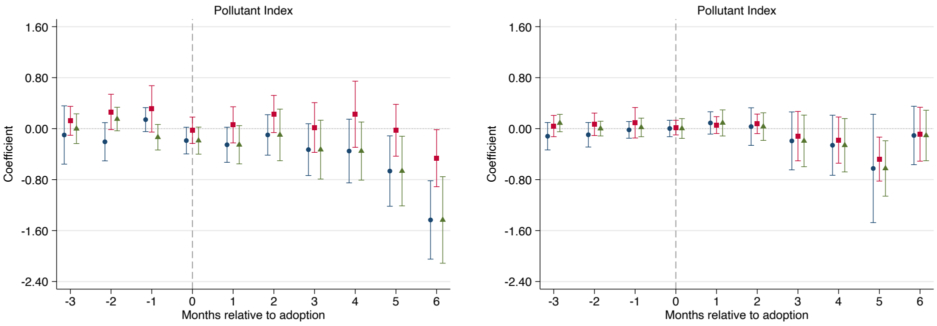
4.4 Further Evidence

The results so far establish that RCS adoption improves river quality on average, with effects that are heterogeneous across cities in ways consistent with the theoretical framework, and robust to a range of alternative specifications. We now turn to three complementary sets of evidence that speak to the mechanisms of how RCS takes effect and where its limits lie. First, we examine whether RCS induced tangible investment in water treatment infrastructure, shedding light on the mechanism through which the reform operates. Second, we ask whether the effects of RCS extend beyond river quality to broader environmental outcomes. Lastly, we document empirical facts to discuss under what conditions Coasian type coordination among neighboring river chiefs under M-form may arise to address the spatial externality.

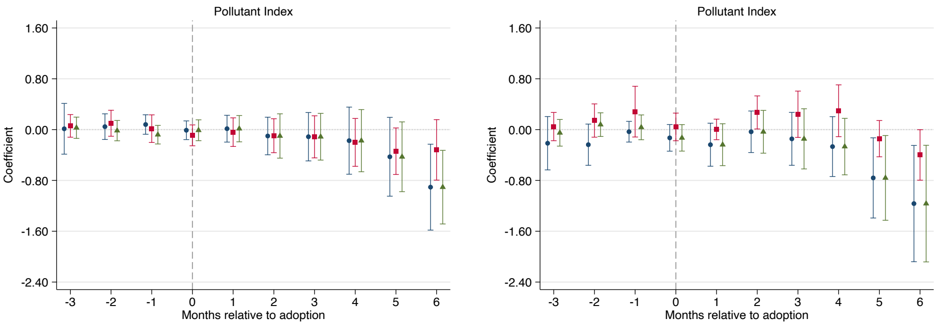
4.4.1 Can RCS Incentivize Infrastructure Investment?

To explore the potential mechanism through which RCS operates, we examine whether the reform induced tangible investment in water treatment infrastructure, which also speaks to whether RCS may have effects extending beyond the six-month post-adoption window to which our difference-in-differences strategy is credibly limited. We draw on data from Zhou et al. (2024) on active underground

Figure 8: Robustness Checks: Alternative Proxies for Externality Intensity



(A) Below (left) and above (right) median composite index for pollution externality



(B) Below (left) and above (right) median wastewater share of industrial output

Notes: This figure plots estimates of the effect of RCS adoption on the pollution index using alternative proxies for externality intensity, using the full sample of monitoring stations. Panel (A) splits cities by a composite index combining average land slope and river sinuosity, where cities below (above) the median composite index face weaker (stronger) spatial externalities. Panel (B) splits cities by the ratio of industrial wastewater discharge to gross industrial output value in the pre-treatment period (2015–2016), where cities below (above) the median wastewater intensity face weaker (stronger) task spillovers. The horizontal axis denotes months relative to RCS adoption. Results are reported for three staggered difference-in-differences estimators: de Chaisemartin and D'Haultfœuille (2020) (circles), Borusyak et al. (2024) (squares), and Callaway and Sant'Anna (2021) (triangles). The sample spans January 2015 to December 2020, excluding cities that adopted RCS before 2015. All specifications include monitoring station and time fixed effects. Confidence intervals are at the 95% level.

Table 2: Effect of RCS Adoption on Underground Wastewater Treatment Infrastructure

	No. of Active Plants			Total Capacity (10^4 m^3/day)		
	BJS	CS	dCdH	BJS	CS	dCdH
RCS	0.034***	0.020**	0.020**	0.653**	0.445*	0.427*
	(0.011)	(0.010)	(0.009)	(0.270)	(0.255)	(0.245)

Notes: This table reports the effect of RCS adoption on underground wastewater treatment plant (UWWTP) infrastructure at the city-year level. The dependent variable in the first three columns is the number of active UWWTPs in a city in a given year. The dependent variable in the last three columns is the total treatment capacity of active UWWTPs, measured in 10^4 cubic meters per day. The key independent variable *RCS* is a binary indicator equal to one once a city has adopted the River Chief System. Results are reported for three staggered difference-in-differences estimators: Borusyak et al. (2024) (BJS), Callaway and Sant'Anna (2021) (CS), and de Chaisemartin and D'Haultfœuille (2020) (dCdH). All specifications include city and year fixed effects. Data on underground wastewater treatment plants are obtained from Zhou et al. (2024). Standard errors clustered at the city level are reported in parentheses: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

wastewater treatment plants (UWWTPs) at the city-year level. Importantly, underground plants eliminate the odour and noise externalities associated with traditional wastewater treatment, making them the preferred technology in densely urbanized areas. Their adoption therefore reflects investment in advanced water management technology, and we ask whether RCS adoption gives political agents stronger incentives to promote such long-term infrastructure investment.

Table 2 reports the estimates of the effect of RCS adoption on the number of active UWWTPs and total treatment capacity (in 10^4 m^3/day) at the city-year level. As before we include city and year fixed effects. RCS adoption is associated with approximately 0.02-0.03 additional active plants and $0.43 - 0.65 \times 10^4$ m^3/day of additional treatment capacity[35]. However, there are a few caveats in interpreting this result: first, the distributions of both outcome variables are highly skewed, with many cities having no active UWWTP. Therefore the estimated effects are likely to be more reflective of accelerated capacity expansion among urbanized cities already investing in such advanced infrastructure[36], where underground plants are most relevant given the costs of odour and noise in densely populated areas. Second, we interpret these estimates as rather suggestive, i.e., one needs to be cautious in giving causal interpretation, since cities might already have been on a trajectory of UWWTP investment and the estimates likely overstate the contribution of RCS[37]. Nevertheless, this at least provides suggestive evidence that organizational structure reform might have generated longer run improvements in treatment capacity that could sustain water quality gains beyond our estimation window.

4.4.2 Can RCS Effects Spill Over to Air Quality?

A well-documented finding in the environmental policy literature is that targeted regulatory reforms tend to improve outcomes along the specific dimensions they address, while leaving non-targeted outcomes unchanged (Kahn et al., 2015). We revisit this theme in the context of River Chief System, and we ask whether the reform generates broad environmental improvements that extend beyond surface water quality, or whether its effects are similarly circumscribed to water pollution only. To this end, we draw on monthly air quality data at the city level from the CASEarth Data Center and estimate the event study specification (24) separately for four air pollutants: $PM_{2.5}$, PM_{10}, SO_2, and NO_2.

Figure 9 presents the results, and an interesting pattern emerges. For SO_2 and NO_2 (bottom row), we observe a gradual and statistically significant reduction following RCS adoption, with both de Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021) estimators pointing to meaningful air pollutant reduction by the sixth month. For $PM_{2.5}$ and PM_{10} (top row), by contrast, there is a modest increase over the same period. To interpret this result, notice first that SO_2 and NO_2 are primarily emitted by stationary heavy industrial sources, i.e., coal-fired plants, chemical factories, and smelters that are also among the main dischargers of industrial wastewater into rivers[38]. Enforcement actions by river chiefs that curtail such activity therefore spill over to reducing air pollutants. $PM_{2.5}$ and PM_{10}, by contrast, originate from a much more diffuse set of

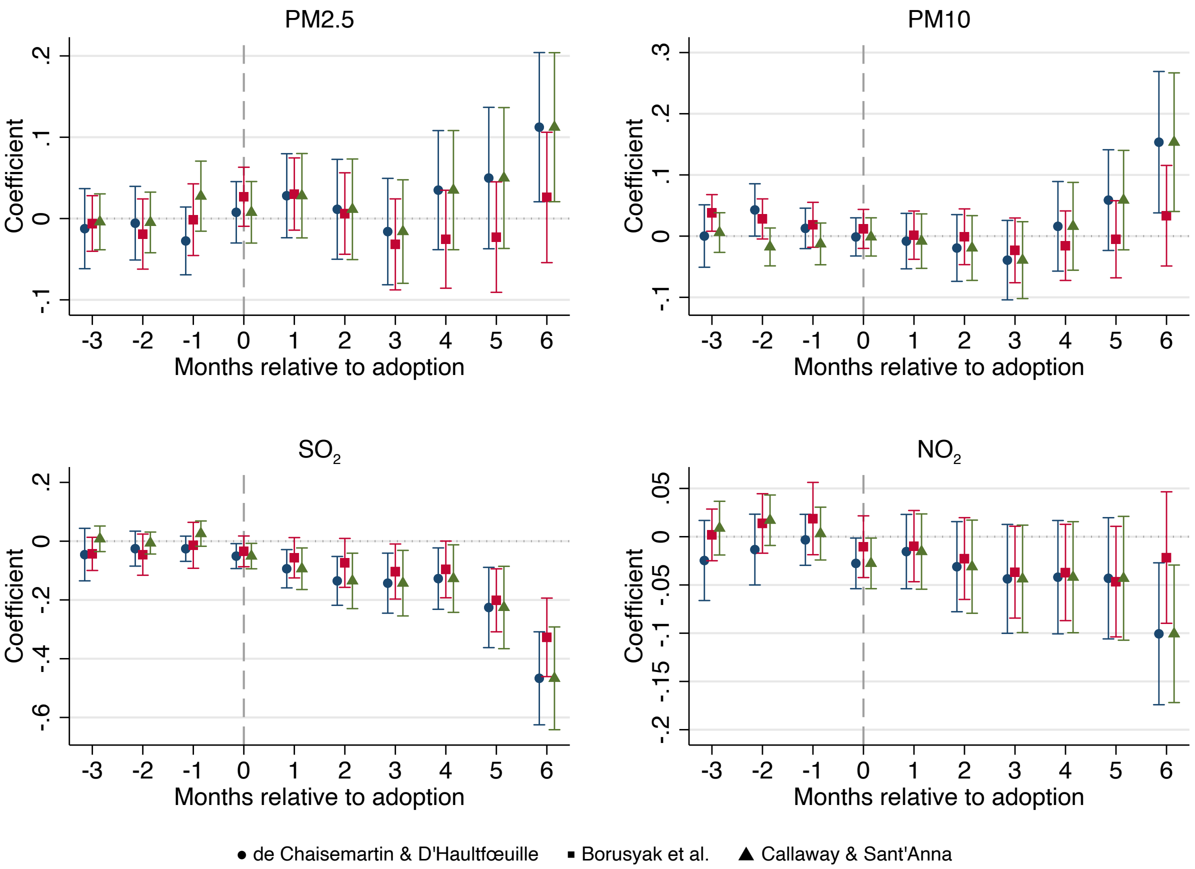
[35] The sample mean of active plants and total capacity are 0.31 and 3.4 (10^4 m^3/day) respectively.

[36] For example, if we use the binary outcome variable, i.e., whether or not the city has UWWTPs, our Callaway and Sant'Anna (2021) and de Chaisemartin and D'Haultfœuille (2020) estimates become statistically insignificant.

[37] Reassuringly, however, augmenting a two-way fixed-effects OLS specification with city-specific linear time trends, which may absorb such differential pre-existing trajectories, still identifies a positive and significant effect of RCS adoption on UWWTP expansion.

[38] See Sing et al. (2023), who document how industrial firms in China generate both water pollution through wastewater discharge and COD measures, and air pollution measured by SO_2 over the years. See also Karplus and Wu (2023) who show that government inspections targeting coal power plants in China led to significant reductions in SO_2 emissions.

Figure 9: The Effects of RCS Adoption on Air Quality



Notes: This figure plots event study estimates of the effect of RCS adoption on air quality across four outcomes: $PM_{2.5}$ (top left), PM_{10} (top right), SO_2 (bottom left), and NO_2 (bottom right). All outcome variables are taken in logarithm. The unit of observation is the city-month. Air quality data are obtained from the CASEarth Data Center and aggregated to monthly frequency. The horizontal axis denotes months relative to RCS adoption. Results are reported for three staggered difference-in-differences estimators: de Chaisemartin and D'Haultfœuille (2020) (circles), Borusyak et al. (2024) (squares), and Callaway and Sant'Anna (2021) (triangles). The sample spans January 2015 to December 2020, excluding cities that adopted RCS before 2015. All specifications include city and time fixed effects. Confidence intervals are at the 95% level.

sources including road dust, vehicle emissions, and biomass burning, which are largely orthogonal to water pollution enforcement[39]. The modest increase in particulate matter may instead reflect a reallocation of bureaucratic effort: in a multitasking environment, as river chiefs shift attention toward water quality management, enforcement of regulations bearing on particulate matter emissions may be crowded out. In other words, by making local leaders explicitly accountable for river quality, RCS may incentivize political agents to reallocate effort away from environmental dimensions not directly covered by the reform.

4.4.3 Can Coasian Bargaining Arise in M-form Organization?

A natural question when externalities are present is why Coasian bargaining between relevant agents cannot restore the first-best outcome, rendering organizational design irrelevant. In our context, this would require upstream and downstream political agents to negotiate directly over pollution levels and reach a mutually beneficial agreement to internalize cross-regional spillovers. Beyond the standard theoretical objections to Coasian reasoning[40], it is also an empirically important question whether, to what extent, and under what conditions such inter-jurisdictional coordination actually occurs under M-form organization. To investigate this, in Appendix B, I provide a theoretical extension of the model in Section 2.2, showing that such Coasian bargaining may arise when the cost of negotiation/coordination is low enough, and the total surplus gains are large enough. Empirically, I manually collect records of joint river inspection events, where river chiefs from neighboring cities voluntarily conduct coordinated patrols and enforcement actions along shared river segments. I interpret this as a direct measure of voluntary coordination among political agents to address cross-regional pollution externalities.[41]

Panel (A) of Figure 10 plots the number of joint inspection events over time. These were virtually absent in the years immediately following RCS adoption, with only 4 events recorded in 2018, but rose markedly thereafter, reaching 71 events by 2024. The majority of these events are within-province, with cross-province joint inspections remaining relatively rare and stable throughout the period. This is consistent with the theoretical argument in the Appendix Section B that provincial boundaries may constitute a barrier to inter-jurisdictional cooperation, with frictions to coordination, whether from lack of common oversight or other transaction costs, considerably higher across provinces than within them.

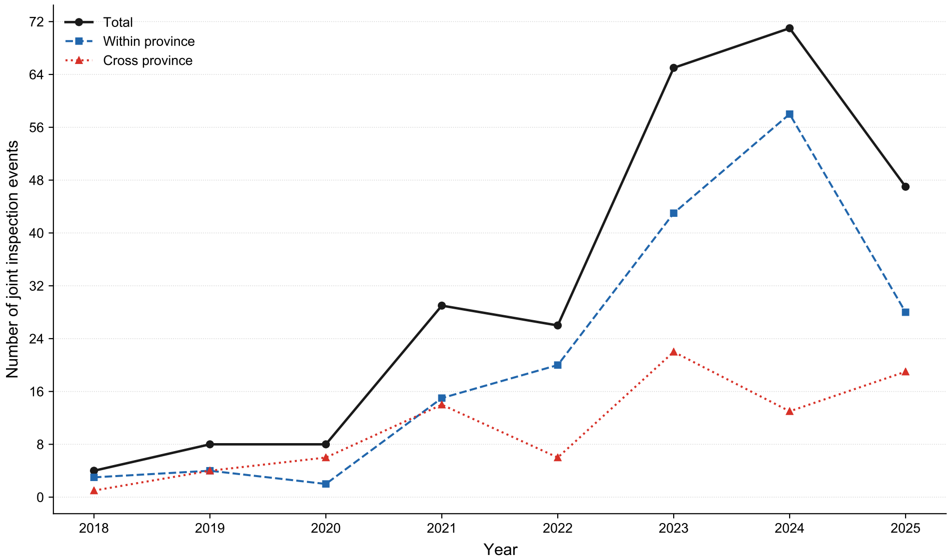
Panel (B) maps the spatial distribution of these events. Cross-province coordination is concentrated along the Yangtze River Delta, particularly among cities in Jiangsu, Zhejiang, and Anhui, as well as Sichuan and Guizhou, regions characterized by dense river networks and also deep economic integration. Within-province coordination is more geographically dispersed, with clusters visible in Shandong, Hunan, Yunnan, and Guangdong. Two conclusions emerge from these descriptive facts. First, voluntary coordination among river chiefs is a real and growing phenomenon, but has emerged primarily after 2020. This is well beyond the 2015–2020 window of our difference-in-differences estimates, suggesting that Coasian-style bargaining was not yet an empirically relevant substitute for organizational reform during our sample period. Furthermore, despite the upward trend, voluntary

[39] See Zhang et al. (2024) for how vehicle emissions and biomass burning become primary contributors to $PM_{2.5}$ in China.

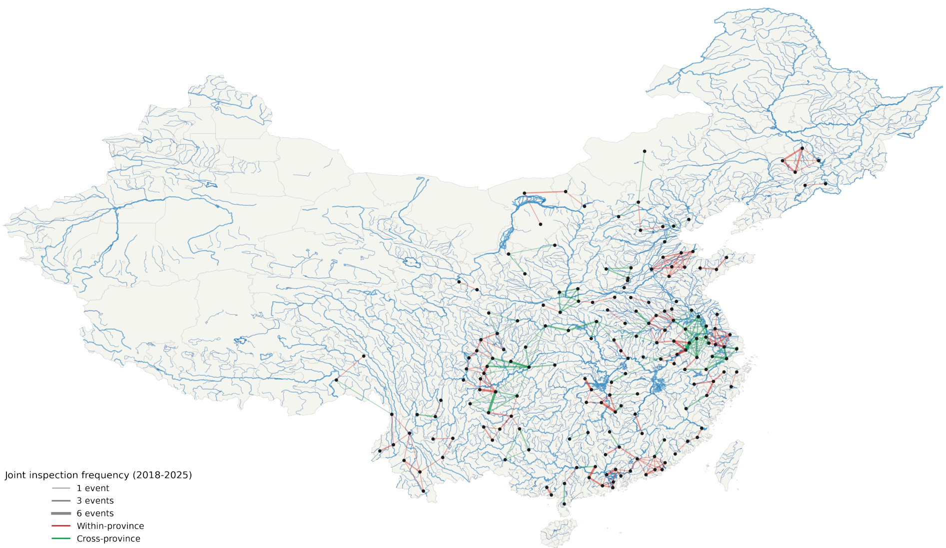
[40] For example, transaction costs, incomplete contracting, and the difficulty of verifying pollution levels across jurisdictions.

[41] Joint inspections typically involve officials from adjacent cities jointly visiting pollution sites, inspecting industrial discharge points, and coordinating enforcement actions along shared river boundaries. Records of such events are published on local government websites. I describe the manual data collection process in Appendix C.

Figure 10: Joint River Inspections Among River Chiefs



(A) Number of Joint Inspection Events by Year



(B) Spatial Distribution of Joint Inspection Events

Notes: Panel (A) plots the number of joint river inspection events over years from 2018 to 2025, distinguishing between within-province inspections (blue dashed line), cross-province inspections (red dotted line), and the total (black solid line). Panel (B) maps the spatial distribution of joint inspection events across cities in China, where red lines connect pairs of cities conducting within-province joint inspections and green lines connect pairs of cities conducting cross-province joint inspections. Joint inspection records are manually collected from local government websites.

coordination remains far from widespread across the country, hence the tradeoff in organization design in internalizing different types of externalities as we discussed earlier in this paper is still relevant. Secondly, the predominance of within-province coordination suggests that shared provincial oversight may facilitate horizontal cooperation among river chiefs. Therefore, fully understanding coordination among political agents in M-form organizations calls for a richer model that incorporates both horizontal and vertical dimensions of bureaucratic interaction, as well as the contracting frictions in Coasian bargaining.

5 Concluding Remarks

This paper develops a simple theory of organizational forms in which political agents are incentivized to internalize different types of environment-related externalities, and provides causal empirical evidence using the staggered rollout of the River Chief System in China. The theory establishes that neither U-form nor M-form bureaucracy achieves the first-best outcome: each internalizes only one type of externality, and the second-best organizational form depends on the relative intensity of the task externality and the regional pollution externality. I further show that yardstick competition, conventionally viewed as an advantage of M-form organization, may exacerbate environmental problems in the presence of asymmetric spatial spillovers.

The empirical evidence supports these theoretical predictions. RCS adoption improves river quality on average, with effects that are heterogeneous across cities in ways consistent with the theory: pollution reductions are larger where the task externality is stronger, the spatial externality is weaker, and river chiefs face lower costs of environmental effort. The role of political competition is nuanced and pollutant-specific, consistent with the theoretical ambiguity between abatement and over-pollution effects. Beyond river quality, RCS induces investment in water treatment infrastructure, generates spillovers to industrial air pollutants, and may crowd out enforcement effort on non-targeted environmental dimensions. Finally, voluntary coordination among river chiefs remains limited in scale and concentrated within provincial boundaries, suggesting that organizational design continues to be a first-order determinant of environmental outcomes even as Coasian-style bargaining gradually emerges.

The findings carry broader implications for the design of environmental governance institutions. The effectiveness of assigning environmental mandates to regional political organizations depends critically on the local economic structure, geography, and the nature of political competition, i.e., factors that vary substantially across contexts. This context-specificity suggests that one-size-fits-all prescriptions for environmental governance are unlikely to be optimal, and that careful attention to the relative intensity of task and regional externalities should inform institutional design.

For future research, firm-level data on pollution, production, and green technology adoption would help quantify the economic costs and benefits of organizational form changes more precisely, and shed light on whether M-form reforms accelerate the structural transformation toward cleaner industries that many developing economies urgently need.

The paper also opens up a broader question: when does political competition foster regional coordination to internalize environmental externalities, and when does it crowd that coordination out? Answering it calls for a richer theoretical framework, for example, extending the stylized model in Appendix B, and more recent pollution data, which together would identify, both theoretically and empirically, what governs the coordination–competition relationship under M-form organizations and whether such coordination materially reduces water pollution.

References

Aghion, P. and Tirole, J. (1995). Some implications of growth for organizational form and ownership structure. *European Economic Review*, 39:440–455.

Anderson, M. L. (2012). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the abecedarian, perry preschool, and early training projects. *Journal of the American Statistical Association*, 103:1481–1495.

Besley, T., Burgess, R., Khan, A., and Xu, G. (2022). Bureaucracy and development. *Annual Review of Economics*, 14:397–424.

Besley, T., Montalvo, J. G., and Reynal-Querol, M. (2011). Do educated leaders matter? *Economic Journal*, 121(554):F205–F227.

Besley, T., Persson, T., and Sturm, D. (2010). Political competition, policy and growth: Theory and evidence from the united states. *Review of Economic Studies*, 77(4):1329–1352.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting event-study designs: Robust and efficient estimation. *Review of Economic Studies*, 91(6):3253–3285.

Brunke, M. and Gonser, T. (1997). The ecological significance of exchange processes between rivers and groundwater. *Freshwater Biology*, 37:1–22.

Burgess, R., Hansen, M., Olken, B., Potapov, P., and Sieber, S. (2012). The political economy of deforestation in the tropics. *Quarterly Journal of Economics*, 127(4):1707–1754.

Cai, H., Chen, Y., and Gong, Q. (2016). Polluting thy neighbor: Unintended consequences of china's pollution reduction mandates. *Journal of Environmental Economics and Management*, 76:86–104.

Callaway, B. and Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Chandler, A. D. (1987). *Strategy and Structure: Chapters in the History of the Industrial Enterprise*. The MIT Press.

Chen, S., Graff-Zivin, J., Wang, H., and Xiong, J. (2025). Combating cross-border externalities: Evidence from china's inter-provincial ecological compensation initiatives. *Journal of Public Economics*, 252:105495.

Chen, Z., Kahn, M., Liu, Y., and Wang, Z. (2018). The consequences of spatially differentiated water pollution regulation in china. *Journal of Environmental Economics and Management*, 88:468–485.

Chien, S.-S. and Hong, D.-L. (2018). River leaders in china: Party-state hierarchy and transboundary governance. *Political Geography*, 62:58–67.

de Chaisemartin, C. and D'Haultføeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

Gadenne, L. and Singhal, M. (2014). Decentralization in developing economies. *Annual Review of Economics*, 6:581–604.

Gao, Q., Xu, H., Tan, X., Liang, J., and Cui, Y. (2022). Impact of agricultural non-point source pollution on river water quality: Evidence from china. *Frontiers in Ecology and Evolution*, 10:858822.

Hashemi Monfared, S. A., Dehghani Darmian, M., Snyder, S. A., Azizyan, G., Pirzadeh, B., and Azhdary Moghaddam, M. (2017). Water quality planning in rivers: Assimilative capacity and dilution flow. *Bulletin of Environmental Contamination and Toxicology*, 99:531–541.

He, G., Wang, S., and Zhang, B. (2016). Surface water quality and infant mortality in china. *Economic Development and Cultural Change*, 65(1):119–139.

He, G., Wang, S., and Zhang, B. (2020). Watering down environmental regulation in china. *Quarterly Journal of Economics*, pages 2135–2185.

Jia, R. (2024). Pollution for promotion. *The Journal of Law, Economics, and Organization.*

Jia, R. and Xu, Y. (2020). Rotating to the top: How career tracks matter in the chinese communist party. Working paper.

Kahn, M., Li, P., and Zhao, D. (2015). Water pollution progress at borders: The role of changes in china's political promotion incentives. *American Economic Journal: Economic Policy*, 7(4):223–242.

Karplus, V. J. and Wu, M. (2023). Dynamic responses of SO_2 pollution to China's environmental inspections. *Proceedings of the National Academy of Sciences*, 120(17).

Kong, D. and Liu, C. (2024). Centralization and regulatory enforcement: Evidence from personnel authority reform in china. *Journal of Public Economics*, page 105030.

Li, H. and Zhou, L.-a. (2005). Political turnover and economic performance: the incentive role of personnel control in china. *Journal of Public Economics*, 89:1743–1762.

Li, J., Shi, X., Wu, H., and Liu, L. (2020). Trade-off between economic development and environmental governance in china: An analysis based on the effect of river chief system. *China Economic Review*, 60:101403.

Lipscomb, M. and Mobarak, A. M. (2017). Decentralization and pollution spillovers: Evidence from the re-drawing of county borders in brazil. *Review of Economic Studies*, 84:464–502.

Liu, Y., Cheng, Y., Li, T., Ni, J., and Norman, S. (2024). Information disclosure and public participation in environmental management: Evidence from the river chief system in china. *China Economic Review*, 85.

Maskin, E., Qian, Y., and Xu, C. (2000). Incentives, information, and organizational form. *Review of Economic Studies*, 67:359–378.

Mu, L., Zhang, C., Zeng, X., Ma, R., Li, Y., and Liu, H. (2025). The impact of the river chief system on transboundary water pollution. *Scientific Reports*, 15(1):8192.

Ostrom, E. (2015). *Governing the Commons: the Evolution of Institutions for Collective Action.* Cambridge University Press.

Ouyang, J., Zhang, K., Wen, B., and Lu, Y. (2020). Top-down and bottom-up approaches to environmental governance in china: Evidence from the river chief system (rcs). *International Journal of Environmental Research and Public Health*, 17:7508.

Qian, Y., Roland, G., and Xu, C. (2006). Coordination and experimentation in m-form and u-form organizations. *Journal of Political Economy*, 114(2):366–402.

Schwab, B., Janzen, S., Magnan, N. P., and Thompson, W. M. (2020). Constructing a summary index using the standardized inverse-covariance weighted average of indicators. *The STATA Journal*, 20(4):952–964.

Shih, V., Adolph, C., and Liu, M. (2012). Getting ahead in the communist party: Explaining the advancement of central committee members in china. *American Political Science Review*, 106(1):166–187.

Sigman, H. (2002). International spillovers and water quality in rivers: Do countries free ride? *American Economic Review*, 92(4):1152–1159.

Sing, T. F., Wang, W., and Zhan, C. (2023). Tracking industry pollution sources and health risks in China. *Nature Scientific Reports*, 13:22232.

State Council (2016). Fully implement river chief system.

Wang, Z., Zhang, Q., and Zhou, L.-A. (2020). Career incentives of city leaders and urban spatial expansion in china. *Review of Economics and Statistics*, 102(5):897–911.

Williamson, O. E. (1975). *Markets and Hierarchies: Analysis and Antitrust Implications: a study in the economics of internal organization*. Free Press.

World Bank (2007). *Cost of Pollution in China: Economic Estimates of Physical Damages*. The World Bank.

World Bank (2018). *Watershed: A New Era of Water Governance in China*. The World Bank.

Xiao, C., Chen, J., Yuan, X., Chen, R., and Song, X. (2020). Model test of the effect of river sinuosity on nitrogen purification efficiency. *Water*, 12(6):1677.

Xu, C. (2011). The fundamental institutions of china's reforms and development. *Journal of Economic Literature*, 49(4):1076–1151.

Zhang, T., Yan, B., Henneman, L., Kinney, P., and Hopke, P. K. (2024). Regulation-driven changes in $PM_{2.5}$ sources in China from 2013 to 2019: A critical review and trend analysis. *Science of the Total Environment*, 934:173091.

Zhou, S., Gong, H., Chen, X., Wang, X., Wang, H., Zhang, Y., Zhu, D., Cao, X., Li, S., and Dai, X. (2024). A dataset of distribution and characterization of underground wastewater treatment plants in China. *Scientific Data*, 11:941.

A Proofs

Proof of Proposition 1.

Step 1: Effort comparisons. The U-form FOC for economic effort is $f'(e^U_{1r}) = e^U_{1r}$, while the surplus optimum has coefficient $(1-\lambda_2) < 1$ for region B and $1 - \lambda_2(2-\delta) < 1$ for region A (by Assumption 1). Since the solution to $\phi f'(e) = e$ is strictly increasing in ϕ by concavity of f, it follows that $e^U_{1r} > e^*_{1r}$ for both regions. An identical argument gives $e^U_{2r} > e^*_{2r}$: the U-form coefficients on g' are 1 and $(2-\delta)$, strictly exceeding the optimum coefficients $(1-\lambda_1)$ and $(2-\delta-\lambda_1)$ respectively.

Step 2: Performance comparisons. We use the notation $\kappa(x) \equiv f(\theta^{-1}(x))$ and $\chi(x) \equiv g(\eta^{-1}(x))$ where $\theta(e) \equiv e/f'(e)$ and $\eta(e) \equiv e/g'(e)$, both increasing by concavity of f and g. Then for region A,

$$\begin{aligned} Q^U_A - Q^*_A &= \left[\lambda_2 f(e^U_{1A}) - g(e^U_{2A})\right] - \left[\lambda_2 f(e^*_{1A}) - g(e^*_{2A})\right] \\ &= \lambda_2\left[\kappa(1) - \kappa(1-\lambda_2(2-\delta))\right] + \left[\chi\left(\frac{2-\delta-\lambda_1}{\omega}\right) - \chi\left(\frac{2-\delta}{\omega}\right)\right], \end{aligned}$$

and

$$Y^U_A - Y^*_A = \left[\kappa(1) - \kappa(1-\lambda_2(2-\delta))\right] + \lambda_1\left[\chi\left(\frac{2-\delta-\lambda_1}{\omega}\right) - \chi\left(\frac{2-\delta}{\omega}\right)\right].$$

For region B

$$\begin{aligned} Q^U_B - Q^*_B &= (1-\delta)\left[Q^U_A - Q^*_A\right] + \lambda_2\left[f(e^U_{1B}) - f(e^*_{1B})\right] + \left[g(e^*_{2B}) - g(e^U_{2B})\right] \\ &= (1-\delta)\left[Q^U_A - Q^*_A\right] + \lambda_2\left[\kappa(1) - \kappa(1-\lambda_2)\right] + \left[\chi\left(\frac{1-\lambda_1}{\omega}\right) - \chi\left(\frac{1}{\omega}\right)\right], \end{aligned}$$

and

$$Y^U_B - Y^*_B = \left[\kappa(1) - \kappa(1-\lambda_2)\right] + \lambda_1\left[\chi\left(\frac{1-\lambda_1}{\omega}\right) - \chi\left(\frac{1}{\omega}\right)\right]$$

It is easy to see that $Q^U_r - Q^*_r$ is decreasing in λ_1 and increasing in λ_2 for $r \in \{A, B\}$, and $Y^U_r - Y^*_r$ is increasing in λ_2 for $r \in \{A, B\}$. To see $Y^U_r - Y^*_r$ is decreasing in λ_1, notice

$$\begin{aligned} \frac{\partial(Y^U_A - Y^*_A)}{\partial\lambda_1} &= \left[\chi\left(\frac{2-\delta-\lambda_1}{\omega}\right) - \chi\left(\frac{2-\delta}{\omega}\right)\right] - \frac{\lambda_1}{\omega}\chi'\left(\frac{2-\delta-\lambda_1}{\omega}\right) < 0; \\ \frac{\partial(Y^U_B - Y^*_B)}{\partial\lambda_1} &= \left[\chi\left(\frac{1-\lambda_1}{\omega}\right) - \chi\left(\frac{1}{\omega}\right)\right] - \frac{\lambda_1}{\omega}\chi'\left(\frac{1-\lambda_1}{\omega}\right) < 0. \end{aligned}$$

Now we discuss how the performance gaps change with δ:

$$\frac{\partial Q^U_A - Q^*_A}{\partial\delta} = -\lambda_2^2\kappa'(1-(2-\delta)\lambda_2) - \frac{1}{\omega}\left[\chi'\left(\frac{2-\delta-\lambda_1}{\omega}\right) - \chi'\left(\frac{2-\delta}{\omega}\right)\right] < 0$$

under Assumption 2. To see this, note first that if η is convex, χ will be concave:

$$\chi''(x) = \frac{(\eta^{-1})'(x)}{[\eta'(\eta^{-1}(x))]^2}\left[g''(\eta^{-1}(x)) - g'(\eta^{-1}(x))\eta''(\eta^{-1}(x))\right] < 0,$$

where the inequality follows from $g'' < 0$ and $\eta'' \geq 0$. Therefore $\chi'\left(\frac{2-\delta-\lambda_1}{\omega}\right) > \chi'\left(\frac{2-\delta}{\omega}\right)$ since $\frac{2-\delta-\lambda_1}{\omega} < \frac{2-\delta}{\omega}$. It then follows that $Q^U_B - Q^*_B$ will also be decreasing in δ if $Q^U_A - Q^*_A > 0$.

Similarly, we have

$$\frac{\partial Y_A^U - Y_A^*}{\partial \delta} = -\lambda_2\kappa'(1-(2-\delta)\lambda_2) - \frac{\lambda_1}{\omega}\left[\chi'\left(\frac{2-\delta-\lambda_1}{\omega}\right) - \chi'\left(\frac{2-\delta}{\omega}\right)\right] < 0$$

This completes the proof. ■

Proof of Proposition 2. Comparing the M-form FOCs to the surplus optimum FOCs, the downstream conditions are identical. So $e_{1B}^M = e_{1B}^*$ and $e_{2B}^M = e_{2B}^*$ follow immediately. For the economic effort in the upstream region, we have $1-\lambda_2(2-\delta) \leq 1-\lambda_2$ for $\delta \in [0,1]$. Since $f'(\cdot)$ is decreasing, we have $e_{1A}^* \leq e_{1A}^M$. For environmental effort, since $(1-\lambda_1)+(1-\delta) \geq 1-\lambda_1$, we have $e_{2A}^* \geq e_{2A}^M$.

The performance implications follow directly. Since $e_{1A}^M \geq e_{1A}^*$ and $e_{2A}^M \leq e_{2A}^*$, we have $Y_A^M = f(e_{1A}^M) - \lambda_1 g(e_{2A}^M) \geq f(e_{1A}^*) - \lambda_1 g(e_{2A}^*) = Y_A^*$. For pollution, $Q_A^M = \lambda_2 f(e_{1A}^M) - g(e_{2A}^M) \geq \lambda_2 f(e_{1A}^*) - g(e_{2A}^*) = Q_A^*$. Since downstream efforts are at the optimum but $Q_A^M \geq Q_A^*$, it follows that $Q_B^M = (1-\delta)Q_A^M + \lambda_2 f(e_{1B}^M) - g(e_{2B}^M) \geq Q_B^*$. ■

Proof of Proposition 3. We could calculate the overall surplus under M-form as

$$\begin{aligned}
S^M &= 2\left[\kappa(1-\lambda_2) - \lambda_1\chi\left(\frac{1-\lambda_1}{\omega}\right)\right] - (3-\delta)\left[\lambda_2\kappa(1-\lambda_2) - \chi\left(\frac{1-\lambda_1}{\omega}\right)\right] \\
&\quad - \left(\theta^{-1}(1-\lambda_2)\right)^2 - \omega\left(\eta^{-1}\left(\frac{1-\lambda_1}{\omega}\right)\right)^2 \\
&= \left[2-(3-\delta)\lambda_2\right]\kappa(1-\lambda_2) - \left[2\lambda_1 - 3 + \delta\right]\chi\left(\frac{1-\lambda_1}{\omega}\right) \\
&\quad - \left(\theta^{-1}(1-\lambda_2)\right)^2 - \omega\left(\eta^{-1}\left(\frac{1-\lambda_1}{\omega}\right)\right)^2
\end{aligned}$$

We can calculate the overall surplus under U-form as

$$\begin{aligned}
S^U &= \kappa(1) - \lambda_1\chi\left(\frac{2-\delta}{\omega}\right) + \kappa(1) - \lambda_1\chi\left(\frac{1}{\omega}\right) - (2-\delta)\left[\lambda_2\kappa(1) - \chi\left(\frac{2-\delta}{\omega}\right)\right] - \left[\lambda_2\kappa(1) - \chi\left(\frac{1}{\omega}\right)\right] \\
&\quad - \left(\theta^{-1}(1)\right)^2 - \frac{1}{2}\omega\left[\left(\eta^{-1}\left(\frac{2-\delta}{\omega}\right)\right)^2 + \left(\eta^{-1}\left(\frac{1}{\omega}\right)\right)^2\right] \\
&= \left[2-(3-\delta)\lambda_2\right]\kappa(1) + (1-\lambda_1)\chi\left(\frac{1}{\omega}\right) + (2-\delta-\lambda_1)\chi\left(\frac{2-\delta}{\omega}\right) \\
&\quad - \left(\theta^{-1}(1)\right)^2 - \frac{1}{2}\omega\left[\left(\eta^{-1}\left(\frac{2-\delta}{\omega}\right)\right)^2 + \left(\eta^{-1}\left(\frac{1}{\omega}\right)\right)^2\right]
\end{aligned}$$

Define $\Delta S = S^M - S^U$. Then we have

$$\begin{aligned}
\Delta S &= \left[(3-\delta)\lambda_2 - 2\right]\left[\kappa(1) - \kappa(1-\lambda_2)\right] + \left[3-\delta-2\lambda_1\right]\chi\left(\frac{1-\lambda_1}{\omega}\right) \\
&\quad -(1-\lambda_1)\chi\left(\frac{1}{\omega}\right) - (2-\delta-\lambda_1)\chi\left(\frac{2-\delta}{\omega}\right) + \left(\theta^{-1}(1)\right)^2 - \left(\theta^{-1}(1-\lambda_2)\right)^2 \\
&\quad +\frac{1}{2}\omega\left[\left(\eta^{-1}\left(\frac{2-\delta}{\omega}\right)\right)^2 + \left(\eta^{-1}\left(\frac{1}{\omega}\right)\right)^2\right] - \omega\left(\eta^{-1}\left(\frac{1-\lambda_1}{\omega}\right)\right)^2
\end{aligned}$$

Differentiate ΔS with respect to λ_2, we have

$$\begin{aligned}
\frac{\partial \Delta S}{\partial \lambda_2} &= (3-\delta)\left[\kappa(1)-\kappa(1-\lambda_2)\right] + \left[(3-\delta)\lambda_2 - 2\right]\kappa'(1-\lambda_2) + 2\theta^{-1}(1-\lambda_2)\left(\theta^{-1}\right)'(1-\lambda_2) \\
&= (3-\delta)\left[\kappa(1)-\kappa(1-\lambda_2)\right] + \left[(3-\delta)\lambda_2 - 2\right] f'\left(\theta^{-1}(1-\lambda_2)\right)\left(\theta^{-1}\right)'(1-\lambda_2) \\
&\quad +2\theta^{-1}(1-\lambda_2)\left(\theta^{-1}\right)'(1-\lambda_2) \\
&= (3-\delta)\left[\kappa(1)-\kappa(1-\lambda_2)\right] + (1-\delta)\lambda_2 f'\left(\theta^{-1}(1-\lambda_2)\right)\left(\theta^{-1}\right)'(1-\lambda_2) > 0.
\end{aligned}$$

Differentiate ΔS with respect to δ, we have

$$\begin{aligned}
\frac{\partial \Delta S}{\partial \delta} &= -\lambda_2\left[\kappa(1)-\kappa(1-\lambda_2)\right] - \chi\left(\frac{1-\lambda_1}{\omega}\right) + \chi\left(\frac{2-\delta}{\omega}\right) + \frac{2-\delta-\lambda_1}{\omega}\chi'\left(\frac{2-\delta}{\omega}\right) \\
&\quad -\eta^{-1}\left(\frac{2-\delta}{\omega}\right)\left(\eta^{-1}\right)'\left(\frac{2-\delta}{\omega}\right) \\
&= -\lambda_2\left[\kappa(1)-\kappa(1-\lambda_2)\right] - \chi\left(\frac{1-\lambda_1}{\omega}\right) + \chi\left(\frac{2-\delta}{\omega}\right) \\
&\quad -\frac{\lambda_1}{\omega} g'\left(\eta^{-1}\left(\frac{2-\delta}{\omega}\right)\right)\left(\eta^{-1}\right)'\left(\frac{2-\delta}{\omega}\right) \\
&= -\lambda_2\left[\kappa(1)-\kappa(1-\lambda_2)\right] - \chi\left(\frac{1-\lambda_1}{\omega}\right) + \chi\left(\frac{2-\delta}{\omega}\right) - \frac{\lambda_1}{\omega}\chi'\left(\frac{2-\delta}{\omega}\right)
\end{aligned}$$

Now to sign $\frac{\partial \Delta S}{\partial \delta}$, notice first that

$$\frac{\partial^2 \Delta S}{\partial \delta \partial \lambda_1} = \frac{1}{\omega}\left[\chi'\left(\frac{1-\lambda_1}{\omega}\right) - \chi'\left(\frac{2-\delta}{\omega}\right)\right] > 0,$$

where the inequality follows from the assumption that $\eta(e)$ is convex in e and therefore $\chi(e)$ is concave in e. Then it follows that

$$\begin{aligned}
\frac{\partial \Delta S}{\partial \delta} &\geq \chi\left(\frac{2-\delta}{\omega}\right) - \chi\left(\frac{1}{\omega}\right) - \lambda_2\left[\kappa(1)-\kappa(1-\lambda_2)\right] \\
&\geq \chi\left(\frac{2-\delta}{\omega}\right) - \chi\left(\frac{1}{\omega}\right) - \kappa(1) + \kappa(0).
\end{aligned}$$

Therefore as long as

$$\delta \leq \delta^* = 2 - \omega\chi^{-1}\left(\chi\left(\frac{1}{\omega}\right) + \kappa(1) - \kappa(0)\right), \tag{25}$$

we have $\frac{\partial \Delta S}{\partial \delta} \geq 0$.

■

Proof of Proposition 4.

Step 1: Effort choices The upstream economic effort choices are $\theta^{-1}(1-\lambda_2(2-\delta))$ for the surplus optimum, $\theta^{-1}(1-\lambda_2)$ for baseline M-form, and $\theta^{-1}(\sigma(1-\lambda_2\delta))$ for yardstick M-form. Since $\delta \in (0,1)$, we have $1-\lambda_2\delta > 1-\lambda_2 > 1-\lambda_2(2-\delta)$, so $e_{1A}^{MC} > e_{1A}^{M} > e_{1A}^{*}$ when $\sigma = 1$. For $\sigma > 1$, $\sigma(1-\lambda_2\delta) > 1-\lambda_2\delta$, further amplifying the distortion.

The Upstream environmental effort choices are $\eta^{-1}\left(\frac{2-\delta-\lambda_1}{\omega}\right)$ for the surplus optimum, $\eta^{-1}\left(\frac{1-\lambda_1}{\omega}\right)$ for baseline M-form, and $\eta^{-1}\left(\frac{\sigma(\delta-\lambda_1)}{\omega}\right)$ for the yardstick M-form. Since $\delta < 1$, we have $\delta - \lambda_1 < 1-\lambda_1 < 2-\delta-\lambda_1$, so $e_{2A}^{MC} < e_{2A}^{M} < e_{2A}^{*}$ when $\sigma = 1$. For $\sigma > 1$, $\sigma(\delta-\lambda_1)$ increases toward $1-\lambda_1$ when $\sigma < \frac{1-\lambda_1}{\delta-\lambda_1}$ and beyond for higher σ. This implies that higher σ may at least partially mitigate the upstream environmental distortion while simultaneously exacerbating the upstream economic distortion.

The downstream economic and environmental effort choices are $\theta^{-1}(\sigma(1-\lambda_2))$ and $\eta^{-1}\left(\frac{\sigma(1-\lambda_1)}{\omega}\right)$. When $\sigma = 1$, these coincide with $\theta^{-1}(1-\lambda_2) = e^*_{1B}$ and $\eta^{-1}\left(\frac{1-\lambda_1}{\omega}\right) = e^*_{2B}$ respectively. For $\sigma > 1$, both coefficients strictly exceed their surplus optimum counterparts, so $e^{MC}_{1B} > e^*_{1B}$ and $e^{MC}_{2B} > e^*_{2B}$.

Step 2 Performance gaps when $\sigma = 1$. We have

$$\begin{aligned} Q^{MC}_A - Q^*_A &= \lambda_2\left[\kappa(1-\lambda_2\delta) - \kappa(1-\lambda_2(2-\delta))\right] + \left[\chi\left(\frac{2-\delta-\lambda_1}{\omega}\right) - \chi\left(\frac{\delta-\lambda_1}{\omega}\right)\right] \;>\; 0, \\ Y^{MC}_A - Y^*_A &= \left[\kappa(1-\lambda_2\delta) - \kappa(1-\lambda_2(2-\delta))\right] + \lambda_1\left[\chi\left(\frac{2-\delta-\lambda_1}{\omega}\right) - \chi\left(\frac{\delta-\lambda_1}{\omega}\right)\right] \;>\; 0, \end{aligned}$$

where both expressions are strictly positive since $1-\lambda_2\delta > 1-\lambda_2(2-\delta)$ and $\frac{2-\delta-\lambda_1}{\omega} > \frac{\delta-\lambda_1}{\omega}$, and κ, χ are increasing. Since downstream efforts coincide with the surplus optimum, $Y^{MC}_B = Y^*_B$ follows immediately, and $Q^{MC}_B - Q^*_B = (1-\delta)(Q^{MC}_A - Q^*_A) \;\geq\; 0$. ■

Proof of Proposition 5. Under baseline M-form, pollution levels are:

$$\begin{aligned} Q^M_A &= \lambda_2\kappa(1-\lambda_2) - \chi\left(\frac{1-\lambda_1}{w}\right); \\ Q^M_B &= (2-\delta)\left[\lambda_2\kappa(1-\lambda_2) - \chi\left(\frac{1-\lambda_1}{w}\right)\right]. \end{aligned}$$

Under U-form, pollution levels are:

$$\begin{aligned} Q^U_A &= \lambda_2\kappa(1) - \chi(2-\delta); \\ Q^U_B &= (1-\delta)\left[\lambda_2\kappa(1) - \chi(2-\delta)\right] + \lambda_2\kappa(1) - \chi(1). \end{aligned}$$

The pollution gaps upon transition from U-form to M-form are therefore:

$$\begin{aligned} \Delta Q_A &= \lambda_2\left[\kappa(1-\lambda_2) - \kappa(1)\right] + \chi(2-\delta) - \chi\left(\frac{1-\lambda_1}{w}\right); \\ \Delta Q_B &= (1-\delta)\Delta Q_A + \lambda_2\left[\kappa(1-\lambda_2) - \kappa(1)\right] + \chi(1) - \chi\left(\frac{1-\lambda_1}{w}\right). \end{aligned}$$

Note that the first term in each expression is negative since $\kappa(1-\lambda_2) < \kappa(1)$, and the second term is positive since $2-\delta > \frac{1-\lambda_1}{w}$ and $1 > \frac{1-\lambda_1}{w}$ respectively, and χ is increasing. The sign of ΔQ_r is therefore ambiguous in general, depending on parameter values.

Part (i): $\frac{\partial \Delta Q_r}{\partial w} > 0$. Since χ is increasing, we have that $\chi\left(\frac{1-\lambda_1}{w}\right)$ is decreasing in w. Since all other terms in ΔQ_A and ΔQ_B do not depend on w, it follows that ΔQ_r is strictly increasing in w for $r \in \{A, B\}$.

Part (ii): $\frac{\partial \Delta Q_r}{\partial \delta} < 0$. For region A:

$$\frac{\partial \Delta Q_A}{\partial \delta} = -\chi'(2-\delta) < 0,$$

since $\chi' > 0$. For region B, rewrite ΔQ_B as:

$$\begin{aligned}\Delta Q_B &= -(2-\delta)\lambda_2\left[\kappa(1)-\kappa(1-\lambda_2)\right]+(1-\delta)\chi(2-\delta)\\ &\quad +\chi(1)-(2-\delta)\chi\left(\frac{1-\lambda_1}{w}\right).\end{aligned}$$

Differentiating with respect to δ:

$$\begin{aligned}\frac{\partial \Delta Q_B}{\partial \delta} &= \lambda_2\left[\kappa(1)-\kappa(1-\lambda_2)\right]-\chi(2-\delta)-(1-\delta)\chi'(2-\delta)+\chi\left(\frac{1-\lambda_1}{w}\right)\\ &\leq -\chi(2-\delta)-(1-\delta)\chi'(2-\delta)+\chi(2-\delta)-\lambda_1\chi'(2-\delta)\\ &= -(1-\delta+\lambda_1)\chi'(2-\delta)<0,\end{aligned}$$

where the inequality uses

$$\lambda_2\left[\kappa(1)-\kappa(1-\lambda_2)\right]+\chi\left(\frac{1-\lambda_1}{w}\right)\leq \chi(2-\delta)-\lambda_1\chi'(2-\delta),$$

which follows from the proof of Proposition 3 under Assumption 2.

Part (iii): $\frac{\partial \Delta Q_r}{\partial \lambda_2}<0$. Differentiating ΔQ_A with respect to λ_2:

$$\frac{\partial \Delta Q_A}{\partial \lambda_2} = \kappa(1-\lambda_2)-\kappa(1)-\lambda_2\kappa'(1-\lambda_2)<0.$$

For region B:

$$\frac{\partial \Delta Q_B}{\partial \lambda_2} = (1-\delta)\frac{\partial \Delta Q_A}{\partial \lambda_2}+\kappa(1-\lambda_2)-\kappa(1)-\lambda_2\kappa'(1-\lambda_2)<0,$$

since both terms are strictly negative.

Part (iv): $\frac{\partial \Delta Q_r}{\partial \sigma}$. We now examine how the pollution change under M-form with yardstick competition varies with the intensity of competition σ. Define $\Delta Q_r^{MC}(\sigma)\equiv Q_r^{MC}(\sigma)-Q_r^U$. Under U-form,

$$Q_A^U=\lambda_2\kappa(1)-\chi(2-\delta),$$

and

$$Q_B^U=(1-\delta)\left[\lambda_2\kappa(1)-\chi(2-\delta)\right]+\lambda_2\kappa(1)-\chi(1).$$

Under M-form with yardstick competition, the effort choices are characterized by

$$e_{1A}^{MC}=\theta^{-1}\left(\sigma(1-\lambda_2\delta)\right),\qquad e_{2A}^{MC}=\eta^{-1}\left(\frac{\sigma(\delta-\lambda_1)}{w}\right),$$

and

$$e_{1B}^{MC}=\theta^{-1}\left(\sigma(1-\lambda_2)\right),\qquad e_{2B}^{MC}=\eta^{-1}\left(\frac{\sigma(1-\lambda_1)}{w}\right).$$

Therefore,

$$Q_A^{MC}(\sigma)=\lambda_2\kappa\left(\sigma(1-\lambda_2\delta)\right)-\chi\left(\frac{\sigma(\delta-\lambda_1)}{w}\right),$$

and

$$Q_B^{MC}(\sigma)=(1-\delta)Q_A^{MC}(\sigma)+\lambda_2\kappa\left(\sigma(1-\lambda_2)\right)-\chi\left(\frac{\sigma(1-\lambda_1)}{w}\right).$$

It follows that

$$\Delta Q_A^{MC}(\sigma) = \lambda_2 \left[\kappa\left(\sigma(1-\lambda_2\delta)\right) - \kappa(1)\right] + \chi(2-\delta) - \chi\left(\frac{\sigma(\delta-\lambda_1)}{w}\right),$$

and

$$\begin{aligned}\Delta Q_B^{MC}(\sigma) =& (1-\delta)\Delta Q_A^{MC}(\sigma) \\ &+ \lambda_2 \left[\kappa\left(\sigma(1-\lambda_2)\right) - \kappa(1)\right] + \chi(1) - \chi\left(\frac{\sigma(1-\lambda_1)}{w}\right).\end{aligned} \tag{26}$$

Differentiating with respect to σ, we obtain

$$\frac{\partial \Delta Q_A^{MC}}{\partial \sigma} = \lambda_2(1-\lambda_2\delta)\kappa'\left(\sigma(1-\lambda_2\delta)\right) - \frac{\delta-\lambda_1}{w}\chi'\left(\frac{\sigma(\delta-\lambda_1)}{w}\right),$$

and

$$\begin{aligned}\frac{\partial \Delta Q_B^{MC}}{\partial \sigma} =& (1-\delta)\frac{\partial \Delta Q_A^{MC}}{\partial \sigma} \\ &+ \lambda_2(1-\lambda_2)\kappa'\left(\sigma(1-\lambda_2)\right) - \frac{1-\lambda_1}{w}\chi'\left(\frac{\sigma(1-\lambda_1)}{w}\right).\end{aligned} \tag{27}$$

Equivalently,

$$\begin{aligned}\frac{\partial \Delta Q_B^{MC}}{\partial \sigma} =& (1-\delta)\left[\lambda_2(1-\lambda_2\delta)\kappa'\left(\sigma(1-\lambda_2\delta)\right) - \frac{\delta-\lambda_1}{w}\chi'\left(\frac{\sigma(\delta-\lambda_1)}{w}\right)\right] \\ &+ \lambda_2(1-\lambda_2)\kappa'\left(\sigma(1-\lambda_2)\right) - \frac{1-\lambda_1}{w}\chi'\left(\frac{\sigma(1-\lambda_1)}{w}\right).\end{aligned} \tag{28}$$

These expressions show that the effect of stronger yardstick competition on pollution is ambiguous in general. A higher σ increases economic effort, which raises pollution, but it also increases environmental effort, which lowers pollution.

We now can give a specific example of functional forms and parameter values such that both sign of $\frac{\partial \Delta Q_r}{\partial \sigma}$ can arise. Consider the following functional forms:

$$f(e) = e^{1/2}, \qquad g(e) = \xi e^{1/2},$$

where $\xi > 0$ governs the effectiveness of environmental effort.

We then have $f'(e) = \frac{1}{2}e^{-1/2}$ and $\theta(e) = \frac{e}{f'(e)} = 2e^{3/2}$. Therefore $\kappa(x) = f(\theta^{-1}(x)) = \left(\frac{x}{2}\right)^{1/3}$ and

$$\kappa'(x) = \frac{1}{3}2^{-1/3}x^{-2/3}.$$

Similarly, $g'(e) = \frac{\xi}{2}e^{-1/2}$, $\eta(e) = \frac{e}{g'(e)} = \frac{2}{\xi}e^{3/2}$, and $\chi(x) = g(\eta^{-1}(x)) = \xi\left(\frac{\xi x}{2}\right)^{1/3} = \xi^{4/3}\left(\frac{x}{2}\right)^{1/3}$. Thus,

$$\chi'(x) = \frac{1}{3}\xi^{4/3}2^{-1/3}x^{-2/3}.$$

Substituting these expressions into the derivative of ΔQ_A^{MC}, we obtain

$$\begin{aligned}\frac{\partial \Delta Q_A^{MC}}{\partial \sigma} &= \lambda_2(1-\lambda_2\delta)\left[\frac{1}{3}2^{-1/3}\left(\sigma(1-\lambda_2\delta)\right)^{-2/3}\right] - \frac{\delta-\lambda_1}{w}\left[\frac{1}{3}\xi^{4/3}2^{-1/3}\left(\frac{\sigma(\delta-\lambda_1)}{w}\right)^{-2/3}\right]\\ &= \frac{1}{3}2^{-1/3}\sigma^{-2/3}\left[\lambda_2(1-\lambda_2\delta)^{1/3} - \xi^{4/3}\left(\frac{\delta-\lambda_1}{w}\right)^{1/3}\right]. \end{aligned} \tag{29}$$

Hence $\frac{\partial \Delta Q_A^{MC}}{\partial \sigma} < 0$ if and only if

$$\xi > (\lambda_2)^{\frac{3}{4}}\left(\frac{(1-\lambda_2\delta)w}{\delta-\lambda_1}\right)^{\frac{1}{4}}$$

Stronger yardstick competition reduces upstream pollution when environmental effort is sufficiently effective, but increases upstream pollution when the pollution generated by economic effort dominates.

Similarly, for downstream pollution, substituting the same functional forms gives

$$\begin{aligned}\frac{\partial \Delta Q_B^{MC}}{\partial \sigma} = \frac{1}{3}2^{-1/3}\sigma^{-2/3}\Bigg\{&(1-\delta)\left[\lambda_2(1-\lambda_2\delta)^{1/3} - \xi^{4/3}\left(\frac{\delta-\lambda_1}{w}\right)^{1/3}\right]\\ &+ \lambda_2(1-\lambda_2)^{1/3} - \xi^{4/3}\left(\frac{1-\lambda_1}{w}\right)^{1/3}\Bigg\}. \end{aligned} \tag{30}$$

Therefore, the sign of $\frac{\partial \Delta Q_B^{MC}}{\partial \sigma}$ is negative if and only if

$$\xi > \frac{(\lambda_2)^{\frac{3}{4}}\left[(1-\delta)(1-\lambda_2\delta)^{1/3} + (1-\lambda_2)^{1/3}\right]^{\frac{3}{4}}}{\left[(1-\delta)\left(\frac{\delta-\lambda_1}{w}\right)^{1/3} + \left(\frac{1-\lambda_1}{w}\right)^{1/3}\right]^{\frac{3}{4}}}$$

and positive when the reverse inequality holds. In fact one can further show that

$$\frac{(\lambda_2)^{\frac{3}{4}}\left[(1-\delta)(1-\lambda_2\delta)^{1/3} + (1-\lambda_2)^{1/3}\right]^{\frac{3}{4}}}{\left[(1-\delta)\left(\frac{\delta-\lambda_1}{w}\right)^{1/3} + \left(\frac{1-\lambda_1}{w}\right)^{1/3}\right]^{\frac{3}{4}}} < (\lambda_2)^{\frac{3}{4}}\left(\frac{(1-\lambda_2\delta)w}{\delta-\lambda_1}\right)^{\frac{1}{4}}.$$

This implies that whenever higher competition reduces upstream ΔQ_A^{MC}, it must reduce downstream ΔQ_B^{MC}. ■

B Coordination under M-form

We consider a simple model to explore when yardstick competition is conducive to coordination among different regional leaders to internalize environment-related externalities.

We begin with the payoff of the river chief in region r as

$$U_r = \beta W_r + \sigma\left(W_r - W_{-r}\right) - \tfrac{1}{2}e_{1r}^2 - \tfrac{1}{2}\omega e_{2r}^2, \qquad W_r \equiv Y_r - Q_r, \tag{31}$$

where W_r is net regional performance, $\beta \geq 0$ is the weight the evaluation system places on absolute (target-based) performance, and $\sigma \geq 0$ the intensity of relative (yardstick) competition. This captures the fact that cadre evaluation under the river chief system rewards both meeting hard water-quality targets and relative ranking against peers. It is also analytically necessary: under a *purely* relative performance objective function, coordination between two agents would simply cancel the (zero-sum) competition term. This general form also captures the earlier model of river chief system: the baseline M-form is $(\beta, \sigma) = (1, 0)$, and the baseline yardstick competition model under M-form is when $\beta = 0$.

Timing The game has two stages. In Stage 1, the upstream and downstream chiefs simultaneously decide whether to coordinate (C) or not (N); coordination requires mutual consent and a transfer from downstream to upstream t, where each agent will also need to incur a fixed cost K. In Stage 2, efforts are chosen under the resulting regime. We solve by backward induction.

Stage 2: non-coordination (N) Each chief chooses effort to maximise U_r taking the other's effort as given. The first-order conditions for the upstream chief are

$$[\beta(1-\lambda_2) + \sigma(1-\lambda_2\delta)]\, f'(e^{\mathsf{N}}_{1A}) = e^{\mathsf{N}}_{1A}, \tag{32}$$
$$[\beta(1-\lambda_1) + \sigma(\delta-\lambda_1)]\, g'(e^{\mathsf{N}}_{2A}) = \omega\, e^{\mathsf{N}}_{2A}, \tag{33}$$

and, since W_A is independent of downstream effort, the downstream conditions are

$$(\beta+\sigma)(1-\lambda_2)\, f'(e^{\mathsf{N}}_{1B}) = e^{\mathsf{N}}_{1B}, \qquad\qquad (\beta+\sigma)(1-\lambda_1)\, g'(e^{\mathsf{N}}_{2B}) = \omega\, e^{\mathsf{N}}_{2B}. \tag{34}$$

The upstream coefficients $(1-\lambda_2\delta)$ and $(\delta-\lambda_1)$ are exactly the distorted weights in the benchmark yardstick competition model, now buffered by the absolute term β: relative competition still induces the strategic exploitation of the spatial externality, but the chief's absolute stake dampens it. We maintain the assumption for $\delta > \lambda_1$ so that upstream environmental effort is interior.

Stage 2: coordination (C) Under coordination the chiefs choose efforts to maximise their *joint* payoff. Because the relative-performance terms are zero-sum between the two regions, they cancel in the sum, leaving

$$S \equiv U_A + U_B = \beta\,(W_A + W_B) - \tfrac{1}{2}\textstyle\sum_r \left(e_{1r}^2 + \omega e_{2r}^2\right). \tag{35}$$

Coordination thus does two things at once: it suppresses the mutually wasteful competition, and it forces each chief to internalise its effect on the *other* region's performance. The first-order conditions for the upstream chief become

$$\beta\,[\,1-\lambda_2(2-\delta)\,]\, f'(e^{\mathsf{C}}_{1A}) = e^{\mathsf{C}}_{1A}, \tag{36}$$
$$\beta\,[\,(1-\lambda_1) + (1-\delta)\,]\, g'(e^{\mathsf{C}}_{2A}) = \omega\, e^{\mathsf{C}}_{2A}, \tag{37}$$

with the downstream conditions $\beta(1-\lambda_2)f'(e^{\mathsf{C}}_{1B}) = e^{\mathsf{C}}_{1B}$ and $\beta(1-\lambda_1)g'(e^{\mathsf{C}}_{2B}) = \omega e^{\mathsf{C}}_{2B}$. Comparing (36)–(37) to the planner's conditions, the coordinated coefficients are precisely β times the surplus-optimal ones.

Stage 1: Coasian bargaining and coordination In the first stage, each river chief will need to first incur a coordination cost $K \geq 0$ if they decide to bargain and cooperate, which captures the friction of organizing and sustaining a joint agreement (meetings, joint monitoring, information sharing, and the enforcement of any side payment). For simplicity, we treat K as an ex-ante, non-bargained entry cost. If the chiefs agree, they implement the coordinated profile e^{C}, and the downstream chief pays the upstream a transfer t; if they disagree, they play the non-cooperative yardstick equilibrium e^{N} of Stage 2, the disagreement point $(U_A^{\mathsf{N}}, U_B^{\mathsf{N}})$.

The transfer solves the generalized Nash bargaining problem with weight $\mu \in (0,1)$ on the upstream chief,

$$t^* = \arg\max_t \left(U_A^{\mathsf{C}} + t - U_A^{\mathsf{N}}\right)^{\mu} \left(U_B^{\mathsf{C}} - t - U_B^{\mathsf{N}}\right)^{1-\mu}. \tag{38}$$

We define the total surplus gains $\Gamma \equiv S^{\mathsf{C}} - S^{\mathsf{N}} \geq 0$ because by definition the effort choices chosen under the coordination regime maximize S^{C}. Then it follows that

$$t^* = \mu\Gamma + \left[U_A^{\mathsf{N}} - U_A^{\mathsf{C}}\right], \tag{39}$$

where $U_A^{\mathsf{N}} - U_A^{\mathsf{C}}$ is upstream chief's *competitive rent*: the payoff it forgoes by abandoning strategic pollution. Furthermore, for the bargaining to take place, we need both

$$\mu\Gamma \geq K, \tag{40}$$

and

$$(1-\mu)\Gamma \geq K, \tag{41}$$

i.e., the net payoff of both political agents to exceed the cost of bargaining. This reduces to a condition which says that coordination can happen only when the total surplus gain is large enough, or the cost of bargaining is small enough

$$K \leq \min\{\mu, 1-\mu\}\Gamma.$$

C Manual Collection of Joint River Inspections

The data collection process was designed to identify publicly available information on inter-municipal cooperation under China's river chief system from 2018 to 2025.

Data were collected in two stages from official government sources. In the first stage, provincial-level water resources or water affairs department websites were searched. Where no dedicated provincial water resources or water affairs website was available, the corresponding provincial government website was used instead. On each website, the built-in search function was used to search separately for the keywords "joint river inspection" and "cross-boundary river". Search results were sorted by relevance, and news reports were screened on the basis of their titles and full-text content. Records were retained only when they involved cooperation among prefecture-level cities. This stage produced 170 relevant records, including 88 records retrieved through the keyword "joint river inspection" and 82 records retrieved through the keyword "cross-boundary river". In the second stage, the same search and screening procedure was applied to prefecture-level municipal water resources or water affairs department websites. Where no dedicated municipal water resources or water affairs website was available, the corresponding municipal government website was used instead. This municipal-level search was conducted to supplement the provincial-level data and to capture more localized reports of inter-municipal cooperation. The second stage yielded 293 relevant records, including 185 records retrieved through the keyword "joint river inspection" and 108 records retrieved through the keyword "cross-boundary river". After combining the records collected from provincial- and municipal-level websites, duplicate reports were removed. The final dataset contains 444 unique records, of which 258 are associated with "joint river inspection" and 186 with "cross-boundary river". We only show the events of "joint river inspection" in the paper because the records involving "cross-boundary river" is more general and noisy.

D Tables and Figures

Table A.1: Balance Table: Pre-Treatment City Characteristics by Adoption Timing

	Late Adopters	Early Adopters	Difference	p-value
Panel A: Pre-treatment water quality				
Log Dissolved Oxygen	2.06	1.96	0.10	0.163
Log Ammonia Nitrogen	-1.19	-1.17	-0.02	0.893
Pollution index	0.39	0.48	-0.09	0.731
Observations	34	31		
Panel B: City characteristics				
Service sector share of GDP (%)	39.01	38.65	0.36	0.781
Service sector employment share (%)	55.25	52.08	3.17	0.188
Log industrial output	16.60	17.04	-0.44	0.014
Wastewater treatment rate (%)	84.18	88.13	-3.96	0.152
Log industrial wastewater discharge	8.35	8.46	-0.11	0.498
Log industrial SO_2 emissions	11.37	11.68	-0.30	0.164
Log industrial dust emissions	10.19	10.38	-0.20	0.344
Log industrial NO_x emissions	10.47	10.61	-0.15	0.313
Domestic waste treatment rate (%)	92.00	91.67	0.33	0.919
Industrial solid waste utilization rate (%)	78.72	86.47	-7.76	0.085
Average slope	13.05	11.72	1.33	0.229
Observations	43	42		

Notes: This table reports pre-treatment city characteristics for early and late adopters of the River Chief System (RCS). Cities are classified as early adopters if they implemented RCS before the sample median adoption month, and late adopters otherwise. Cities that had already adopted RCS by January 2015 are excluded. The difference column reports the mean difference (late minus early), with the corresponding p-value from a two-sample t-test. Panel A reports pre-treatment water-quality outcomes, each constructed as the 2015 average across a city's monitoring stations: log dissolved oxygen and log ammonia nitrogen (mg/L) and the composite water quality index used in the main analysis. The permanganate index is omitted from the pre-treatment comparison because it is reported for only a minority of stations in 2015. Panel A is restricted to the 65 cities (34 late, 31 early) with monitoring coverage in 2015; the remaining cities lack a pre-treatment water-quality baseline and enter the analysis only through the characteristics in Panel B. Panel B characteristics are measured in 2015 from the Chinese City Statistical Yearbook. Log industrial output is the log of gross industrial output value (current prices, 10,000 RMB). Industrial wastewater discharge is in 10,000 tonnes; SO_2, NO_x and dust emissions are in tonnes. The domestic waste treatment rate and industrial solid waste utilization rate are in percentages. Average slope is a time-invariant land-slope variable from the National Earth System Science Data Center.

Table A.2: Determinants of RCS Adoption Timing

	(1) Early	(2) Early	(3) Early	(4) Early
Service sector share of GDP (%)	−0.0138	0.0094	−0.0085	0.0036
	(0.0108)	(0.0063)	(0.0111)	(0.0083)
Service sector employment share (%)	0.0011	−0.0055	0.0039	−0.0049
	(0.0071)	(0.0073)	(0.0064)	(0.0097)
Log industrial output	0.173**	0.0343	0.147	0.0916
	(0.0772)	(0.0575)	(0.0965)	(0.0658)
Wastewater treatment rate (%)	0.0026	0.0022	0.0057	0.0032
	(0.0052)	(0.0031)	(0.0048)	(0.0028)
Log industrial wastewater discharge	−0.0244	−0.0993	0.0008	−0.0782
	(0.0995)	(0.0600)	(0.147)	(0.0779)
Log industrial SO_2 emissions	0.128	0.0494	0.348*	0.0827
	(0.0881)	(0.0517)	(0.186)	(0.197)
Log industrial dust emissions	0.0134	−0.0213	−0.129	−0.0924
	(0.0532)	(0.0385)	(0.108)	(0.114)
Log industrial NO_x emissions	−0.0806	−0.0112	−0.412	−0.144
	(0.139)	(0.0836)	(0.311)	(0.290)
Waste treatment rate (%)	−0.0013	−0.0081*	0.0011	−0.0083
	(0.0049)	(0.0040)	(0.0042)	(0.0076)
Solid waste utilization rate (%)	0.0029	−0.0007	0.0003	0.0002
	(0.0031)	(0.0027)	(0.0040)	(0.0044)
Average slope	−0.0076	−0.0251	−0.0182	−0.0330
	(0.0186)	(0.0192)	(0.0219)	(0.0190)
Pre-treatment water quality				
Log dissolved oxygen			−0.574	−0.0620
			(0.427)	(0.406)
Log ammonia nitrogen			0.0757	−0.0261
			(0.133)	(0.167)
Water quality index			−0.279*	−0.145
			(0.142)	(0.159)
Constant	−2.776	1.362	0.666	2.165
	(2.058)	(2.095)	(2.145)	(2.062)
Province fixed effects	No	Yes	No	Yes
Pre-treatment controls	No	No	Yes	Yes
Observations	82	79	61	58
Adjusted R^2	0.041	0.587	0.102	0.480

Notes: This table reports OLS estimates of a linear probability model where the dependent variable equals one if a city is an early adopter of the River Chief System (RCS), and zero otherwise. Early adopters are cities that implemented RCS before the sample median adoption month. Cities that had already adopted RCS by January 2015 are excluded. Columns (1) and (3) include no province fixed effects; columns (2) and (4) absorb province fixed effects. Columns (3) and (4) add pre-treatment water-quality controls: log dissolved oxygen, log ammonia nitrogen, and the composite water quality index, each measured as the 2015 average across a city's monitoring stations. The sample falls from 79–82 cities in columns (1)–(2) to 58–61 in columns (3)–(4) because only cities with 2015 monitoring coverage have a pre-treatment water-quality baseline. All city characteristics are measured in 2015 from the Chinese City Statistical Yearbook; average slope is a time-invariant land-slope variable from the National Earth System Science Data Center. Standard errors clustered at the province level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Correlation of Heterogeneity Proxies

	Education	Slope	Service Share	Competition
Education	1.000			
Slope	−0.129	1.000		
Service share	−0.098	−0.309	1.000	
Competition	−0.072	−0.693	0.241	1.000

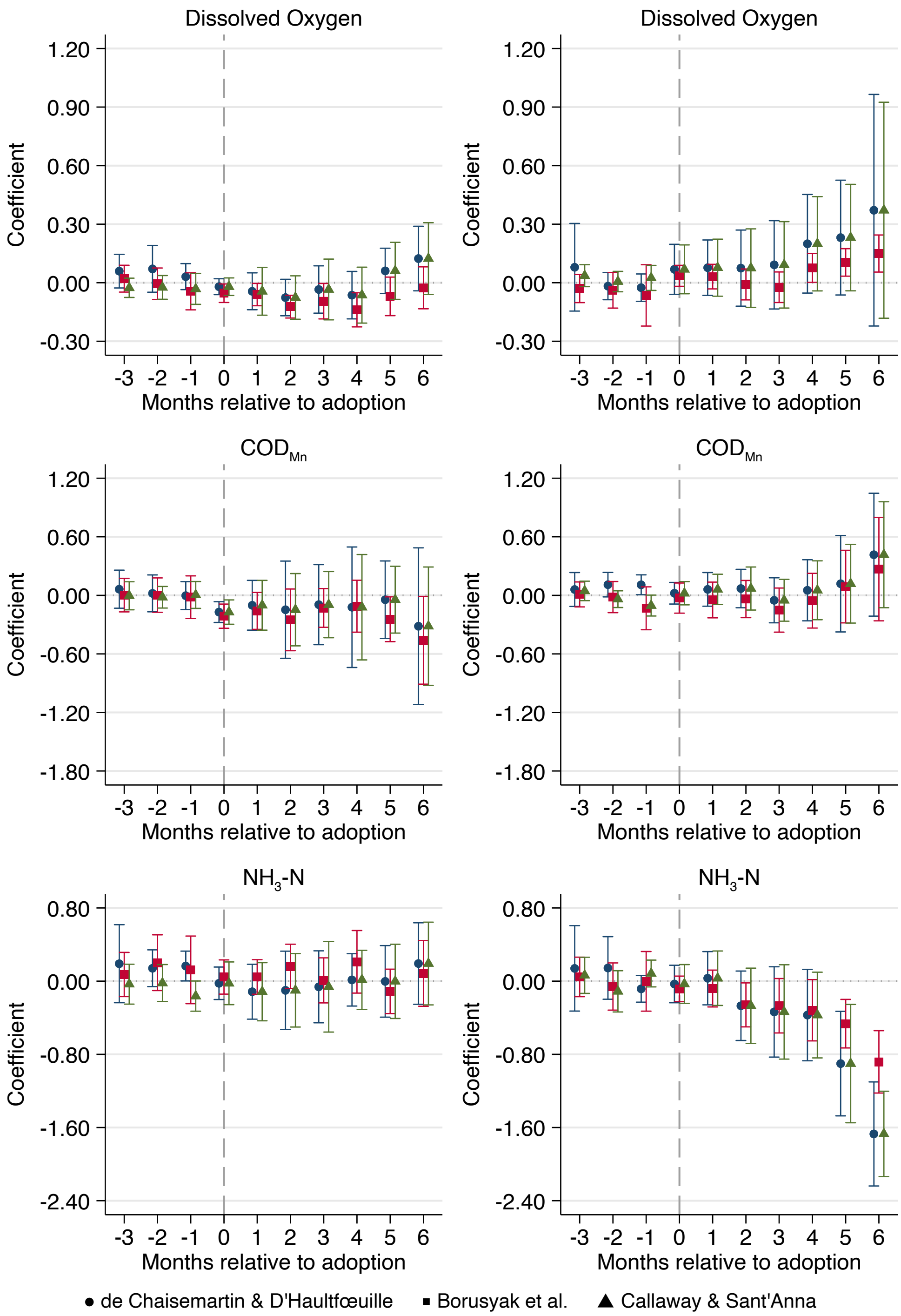
Notes: This table reports tetrachoric correlations among the four binary proxies used in the heterogeneity analysis, computed across cities that adopted the River Chief System within the sample window. *Education* equals one for cities ever led during treatment by a river chief holding a full-time master's or PhD degree; *Slope* for above-median average land slope; *Service share* for above-median service-sector share of GDP; and *Competition* for cities which are ever located in a high-competition province during the years when RCS is in place.

Table A.4: Heterogeneous Effects of RCS Adoption on the Pollutant Index

	Low	High	Difference (High − Low)
Education	−0.226	−0.280	−0.054
	(0.181)	(0.210)	
Slope	−0.588***	−0.126	0.462
	(0.164)	(0.148)	
Service share	−0.582***	−0.184	0.398
	(0.216)	(0.187)	
Competition	−0.358*	−0.356*	0.001
	(0.198)	(0.197)	

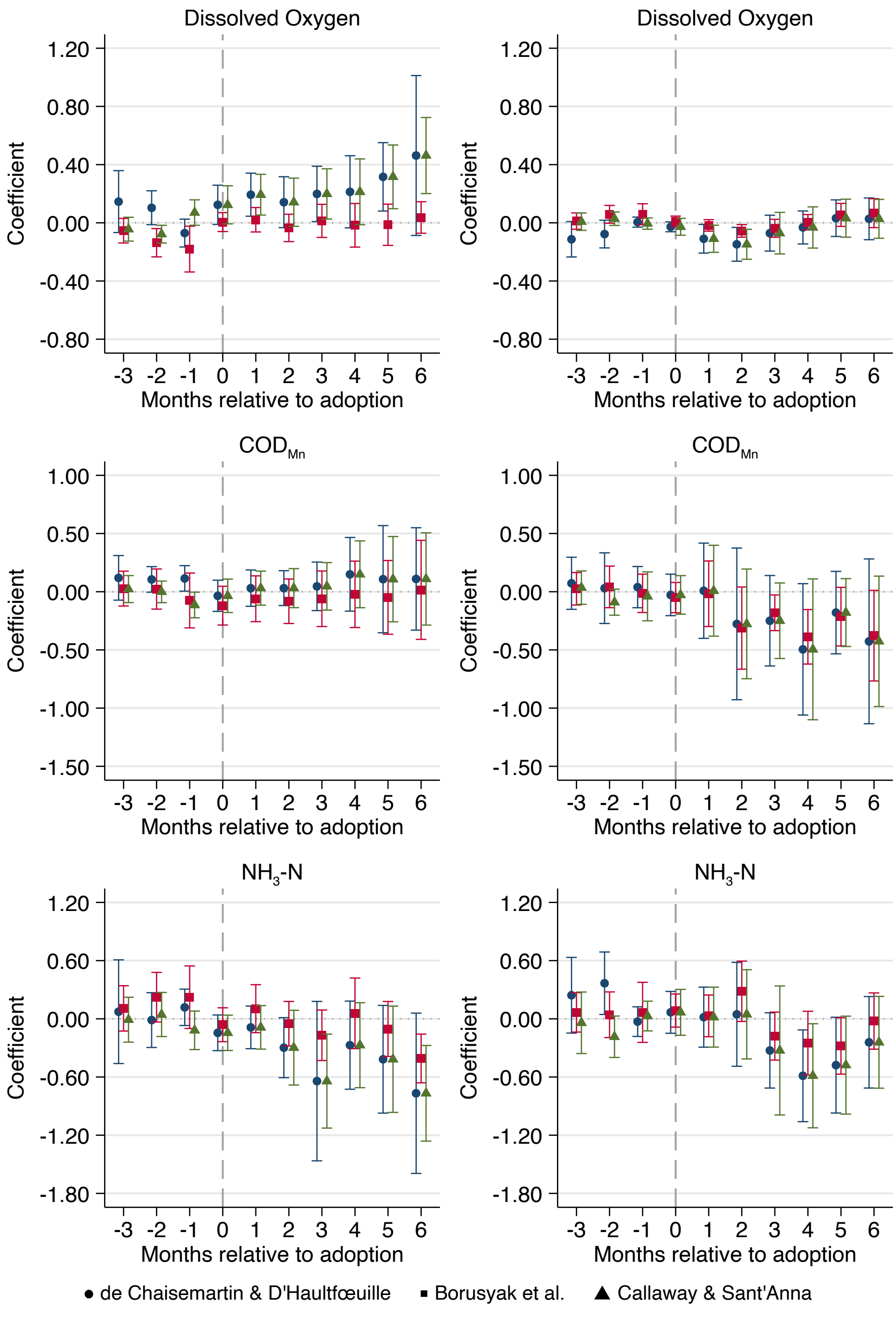
Notes: Each entry is the average treatment effect of RCS adoption on the pollutant index, estimated using the Callaway and Sant'Anna (2021) estimator, separately for the Low and High group of each moderator. The last column reports the High-minus-Low difference. "High" denotes, respectively: having a river chief with postgraduate education during treatment (row. 1); above-median land slope (row. 2); above-median service-sector share of GDP (row. 3); and operating in a province-year with low age dispersion among river chiefs, our proxy for intense political competition (row. 4). "Low" is the complement in each case. All specifications include monitoring-station and month fixed effects; standard errors clustered at the city level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure A.1: Heterogeneous Effects of RCS Adoption by River Chief Education



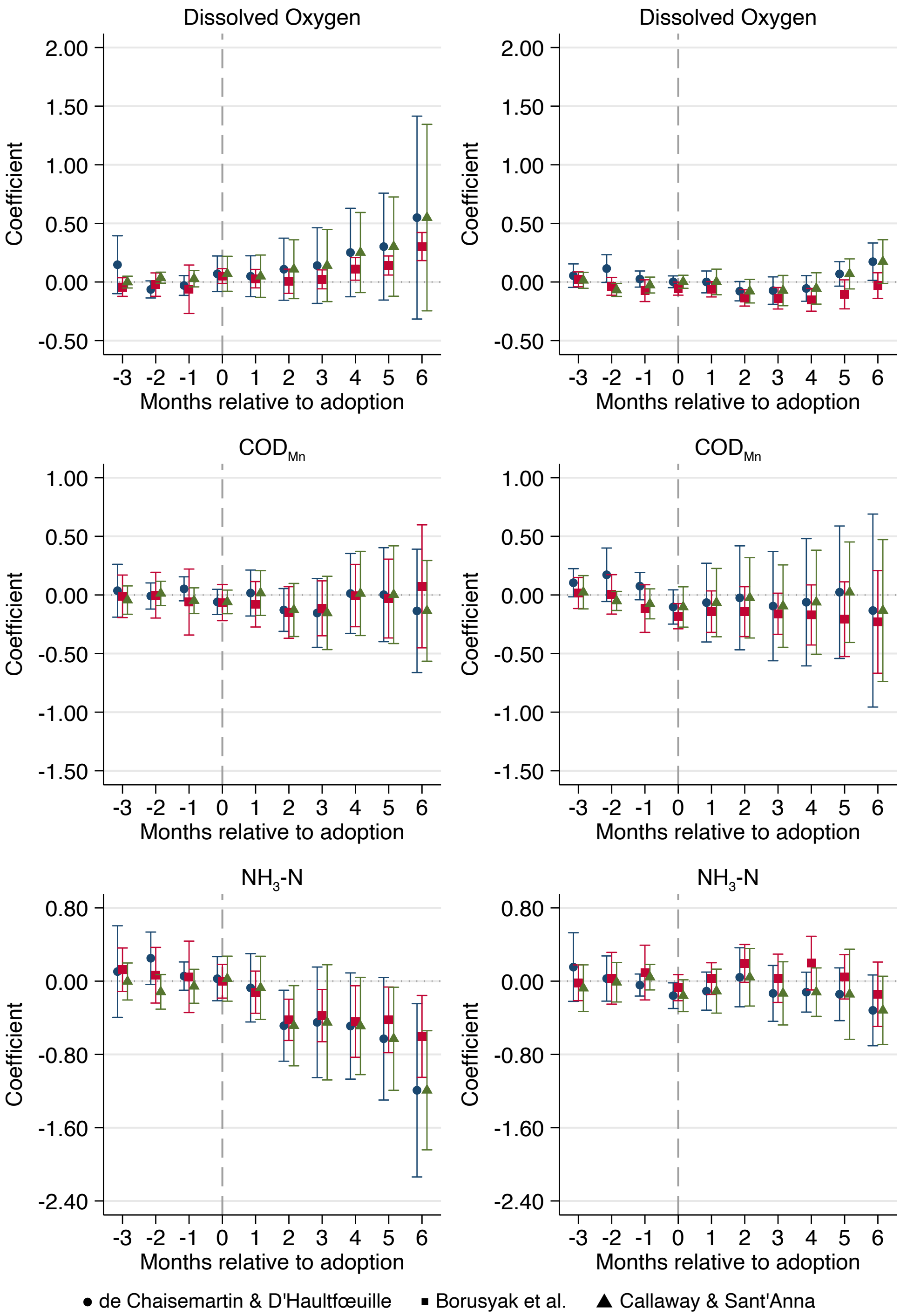
Notes: This figure plots estimates of the heterogeneous effect of RCS adoption on river quality by river chief educational attainment. The right column shows estimates for cities led by a river chief with at least a full-time master's or PhD degree ($\text{Education}_c = 1$); the left column shows estimates for cities whose river chiefs do not meet this threshold ($\text{Education}_c = 0$). Each row corresponds to a different outcome: dissolved oxygen, permanganate index (COD_{Mn}), and ammonia nitrogen (NH_3-N). The horizontal axis denotes months relative to RCS adoption. Results are reported for three staggered difference-in-differences estimators: de Chaisemartin and D'Haultfœuille (2020) (circles), Borusyak et al. (2024) (squares), and Callaway and Sant'Anna (2021) (triangles). The sample spans January 2015 to December 2020, excluding cities that adopted RCS before 2015. All specifications include monitoring station and time fixed effects. Confidence intervals are at the 95% level.

Figure A.2: Heterogeneous Effects of RCS Adoption by Land Slope



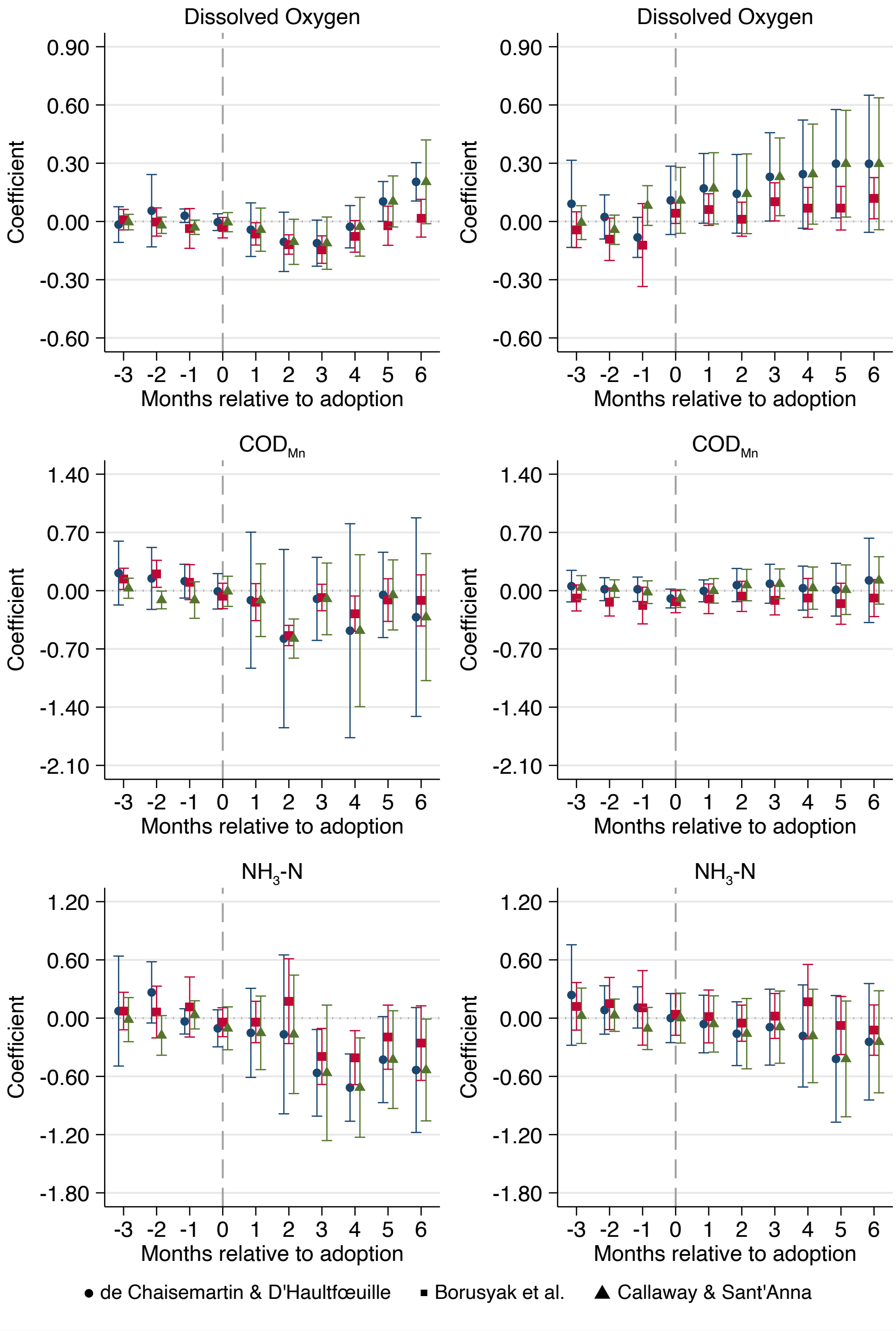
Notes: This figure plots estimates of the heterogeneous effect of RCS adoption on river quality by city land slope. The right column shows estimates for cities above the median land slope ($\text{Slope}_c = 1$), which face more salient cross-regional pollution externalities; the left column shows estimates for cities below the median land slope ($\text{Slope}_c = 0$). Each row corresponds to a different outcome: dissolved oxygen, permanganate index (COD_{Mn}), and ammonia nitrogen (NH_3-N). The horizontal axis denotes months relative to RCS adoption. Results are reported for three staggered difference-in-differences estimators: de Chaisemartin and D'Haultfœuille (2020) (circles), Borusyak et al. (2024) (squares), and Callaway and Sant'Anna (2021) (triangles). The sample spans January 2015 to December 2020, excluding cities that adopted RCS before 2015. All specifications include monitoring station and time fixed effects. Confidence intervals are at the 95% level.

Figure A.3: Heterogeneous Effects of RCS Adoption by Service Sector Share



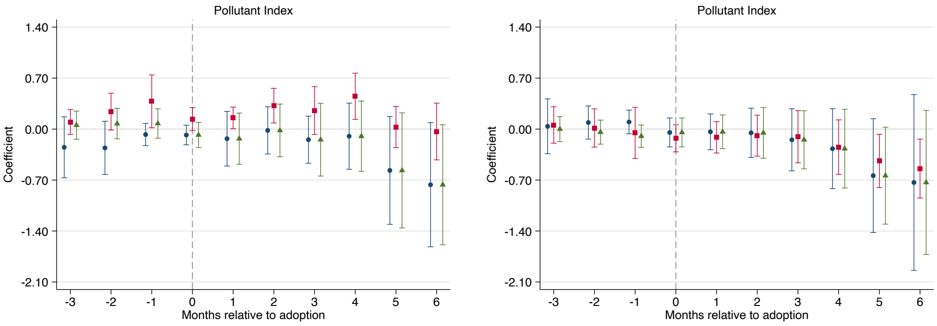
Notes: This figure plots estimates of the heterogeneous effect of RCS adoption on river quality by the service sector share of local GDP. The right column shows estimates for cities above the median service sector share ($\text{ServiceShare}_c = 1$), which rely less heavily on polluting industrial and agricultural activity and therefore face weaker spillovers from economic promotion to environmental outcomes; the left column shows estimates for cities below the median service sector share ($\text{ServiceShare}_c = 0$). Each row corresponds to a different outcome: dissolved oxygen, permanganate index (COD_{Mn}), and ammonia nitrogen (NH_3-N). The horizontal axis denotes months relative to RCS adoption. Results are reported for three staggered difference-in-differences estimators: de Chaisemartin and D'Haultfœuille (2020) (circles), Borusyak et al. (2024) (squares), and Callaway and Sant'Anna (2021) (triangles). The sample spans January 2015 to December 2020, excluding cities that adopted RCS before 2015. All specifications include monitoring station and time fixed effects. Confidence intervals are at the 95% level.

Figure A.4: Heterogeneous Effects of RCS Adoption by Political Competition

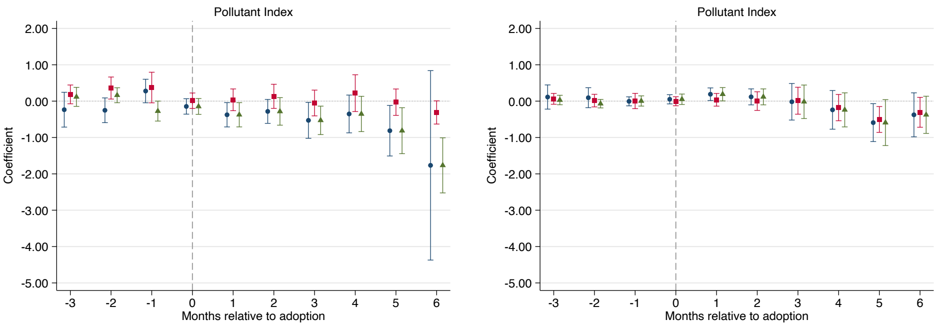


Notes: This figure plots estimates of the heterogeneous effect of RCS adoption on river quality by the degree of political competition. The right column shows estimates for cities in high-competition provinces ($\text{Competition}_c = 1$), defined as provinces where the within-province standard deviation of river chiefs' ages falls below the sample median; the left column shows estimates for cities in low-competition provinces ($\text{Competition}_c = 0$). Each row corresponds to a different outcome: dissolved oxygen, permanganate index (COD_{Mn}), and ammonia nitrogen (NH_3-N). The horizontal axis denotes months relative to RCS adoption. Results are reported for three staggered difference-in-differences estimators: de Chaisemartin and D'Haultføeuille (2020) (circles), Borusyak et al. (2024) (squares), and Callaway and Sant'Anna (2021) (triangles). The sample spans January 2015 to December 2020, excluding cities that adopted RCS before 2015. All specifications include monitoring station and time fixed effects. Confidence intervals are at the 95% level.

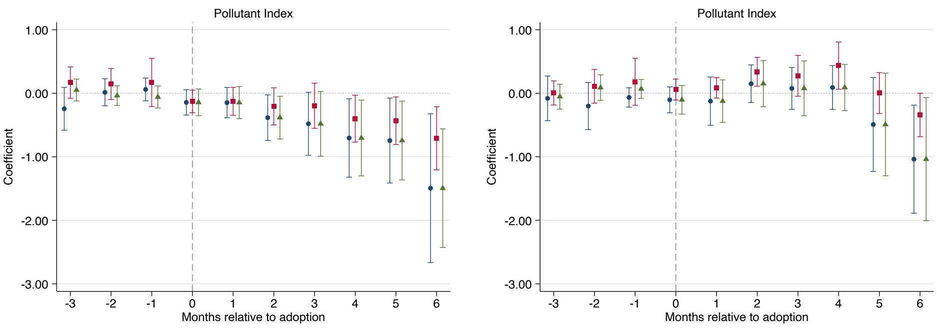
Figure A.5: Heterogeneous Effects of RCS Adoption on Pollution Index (Subsample)



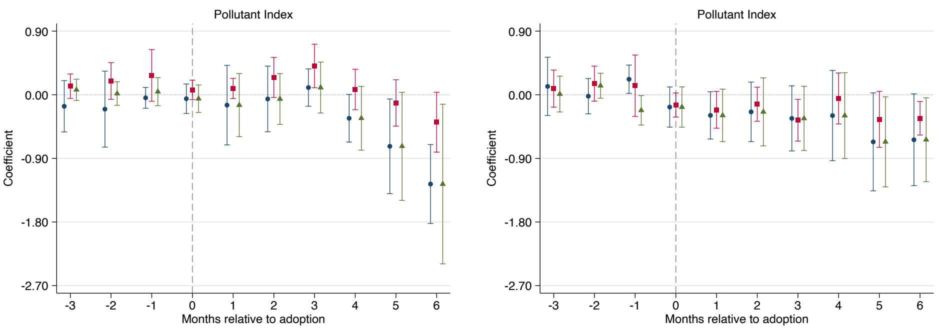
(A) Below (left) and above (right) master's degree



(B) Below (left) and above (right) median land slope



(C) Below (left) and above (right) median service sector share of GDP



(D) Low (left) and high (right) political competition

Notes: This figure plots estimates of the heterogeneous effect of RCS adoption on the pollution index, using the subsample of monitoring stations. Panel (A) splits cities by river chief educational attainment (below vs above master's degree). Panel (B) splits cities by median land slope. Panel (C) splits cities by median service sector share of GDP. Panel (D) splits cities by the degree of political competition. The horizontal axis denotes months relative to RCS adoption. Results are reported for three staggered difference-in-differences estimators: de Chaisemartin and D'Haultfœuille (2020) (circles), Borusyak et al. (2024) (squares), and Callaway and Sant'Anna (2021) (triangles). The sample spans January 2015 to December 2020, excluding cities that adopted RCS before 2015. All specifications include monitoring station and time fixed effects. Confidence intervals are at the 95% level.